# MULTI-CRITERIA OPTIMISATION OF GROUP REPLACEMENT SCHEDULES FOR DISTRIBUTED WATER PIPELINE ASSETS

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Reliability Analysis, Hazard Models, Multi-Criteria Optimisation, Pipeline Maintenance, Decision Support, Cost Modelling, Service Interruption Modelling, Group Replacement Scheduling

# Abstract

Pipes in underground water distribution systems deteriorate over time. Replacement of deteriorated water pipes is often a capital-intensive decision for utility companies. Replacement planning aims to minimise total costs while maintaining a satisfactory level of services.

This candidature presents an optimization model for group replacement schedules of water pipelines. Throughout this thesis this model is referred to as **RDOM-GS, i.e., Replacement Decision Optimisation Model for Group Scheduling**. This candidature also presents an improved hazard modelling method for predicting the reliability of water pipelines, which can be applied to calculate the total costs and total service interruptions in RDOM-GS. These new models and methodology are designed to improve the accuracy of reliability prediction and provide a new approach to optimising schedules for replacement of groups of water pipelines.

A comprehensive literature review covering the reliability analysis and replacement optimisation of water pipes has revealed the following limitations of the current state-of-the-art: (1) In practice, replacement of water pipelines is usually scheduled into groups based on expert experience in order to reduce maintenance costs. However, existing research on water pipe replacement optimisation focuses on individual pipes. (2) Pipe networks are a mix of different pipe materials, diameters, length and other operating environmental conditions. However, an effective approach to statistical grouping has not yet been developed in the reliability analyses for water pipes.

RDOM-GS optimises replacement schedules by considering three group-scheduling criteria: shortest geographic distance, maximum replacement equipment utilization, and minimum service interruption. In order to be able to reach an optimal replacement solution considering group scheduling, a modified evolutionary optimisation algorithm was developed in this thesis and integrated with the RDOM-GS. By integrating new cost functions, a model of service interruption, and optimisation algorithms into a unified procedure, RDOM-GS is able to deliver

replacement schedules minimising total life-cycle cost, and conditionally keeping service interruptions under a specified limit.

The proposed improved hazard modelling method for water pipes has three improvements on existing methods: (1) it can systematically partition water pipeline data into relatively homogeneous statistical groups through developing a statistical grouping algorithm; (2) it can reduce the underestimation effects caused by real life data through developing a modified empirical hazard model; (3) it can differentiate the application impacts of two commonly used empirical hazard formulas through a comparative study. This candidature proposes a Monte Carlo simulation framework of water pipelines to generate test-bed sample data sets that characterises primary features of the real-world data. The framework enables the evaluation the hazard modelling method for censored data.

These newly developed methodologies/models have been verified using simulations and industrial case studies. The results of the industrial case study show that the methodologies and models proposed in this candidature can effectively improve replacement planning of water pipes by considering multi-criteria group scheduling. Also, total life-cycle costs can be reduced by 5%, as well as a reduction by 11.25% on service interruptions.

The research outcomes of this candidature are expected to enrich the body of knowledge in the field of optimal replacement of water pipes, where group scheduling based on multiple criteria is considered in water-pipe replacement decisions. RDOM-GS combined with cost analysis, service interruption analysis and optimisation analysis is able to deliver optimised replacement schedules in order to reduce investment costs and service interruptions. Additionally, by applying the improved hazard modelling method, water pipeline data can systematically be grouped by their specific features, so that the accuracy of reliability analysis considering pipe segments can be enhanced.

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# Nomenclature

## *Abbreviations*

| | |
|---|---|
| AFR | Average failure rate |
| AHP | Analytic hierarchy process |
| ANN | Artificial neural network |
| ANOVA | Analysis of variance |
| AWWA | The American Water Works Association |
| cdf | Cumulative distribution function |
| CIEAM | Cooperative Research Centre for Infrastructure and Engineering Asset Management |
| CM | Corrective maintenance |
| DSM | Distributed Scheduling Model |
| EA | Evolutionary algorithm |
| GA | Genetic algorithm |
| GSOP | Group scheduling optimisation problem |
| GIS | Geographic information system |
| I-WARP | Individual Water Main Renewal Planner |
| MACROS | Multi-objective Automated Construction Resource Optimization System |
| MLE | Maximum likelihood estimation |
| MOEA | Multi-objective evolutionary algorithm |
| ME-BMS | Multiple-element bridge management system |
| MOGA | Multi-objective genetic algorithm |
| MTTF | Mean Time To Failure |
| NHPP | Non-Homogeneous Poisson Process |
| NORP100M | Number of repairs per 100 metres |
| NPGA | Niched Pareto genetic algorithm |
| NSGA | Non-dominated sorting genetic algorithm |
| NSGA-II | Non-dominated sorting genetic algorithm-II |
| pdf | Probability density function |

| | |
|---|---|
| PM | Preventative maintenance |
| PdM | Predictive maintenance |
| RBPM | Reliability based preventive maintenance |
| RDOM-GS | Replacement decision optimisation model for group scheduling |
| ROCOF | Rate of failure occurrence |
| SPEA | Strength Pareto Evolutionary Algorithm |
| TBPM | Time based preventive maintenance |
| TTR | Time to replacement |

## *Notations*

*Roman Letters*

$currD$ Current date

$C_{d,i}$ Transportation cost of pipe *i*

$C_{fail}$ Cost incurred due to a pipe segment failure

$C_{repl}$ Cost of replacement of one pipe

$C_{i,t}^{tot}$ Total cost for replacing pipe *i* at its calendar year *t* during the planning horizon *T*

$C_{fail,i,t}^{tot}$ Failure cost for replacing pipe *i* at its calendar year *t* during the planning horizon *T*

$C_{l,i}$ Pipe preparation cost of pipe *i*

$C_{M,i}$ Machinery and labours cost of pipe *i*

$C_{repl,i,t}^{tot}$ Total replacement cost for replacing pipe *i* at its calendar year *t* during the planning horizon *T*

$\overline{C}_{repl,i}$ Replacement cost of pipe *i* for group scheduling

$Cv_i$ Unit cost for transportation for replacing pipe *i*

$CL_i$ Length cost rate

$CM_i$ Unit cost of machinery for replacing pipe *i*

$CSL_i$ Unit cost of skilled labour for replacing pipe *i*

$\overline{C}_{d,i}$ Transportation cost of pipe *i* for group scheduling

$\overline{C}_{M,i}$ Machinery and labour cost of pipe *i* for group scheduling

$d_i$ $N(t_i) - N(t_{i+1})$

$dis_i$ Transportation distance for replacing pipe *i*

$D_i$ Diameter of pipe *i*

$Dr_{c,i}$ Duration of replacement of pipe *i*

| | |
|---|---|
| $f(t)$ | Probability density function |
| $f_{crp}$ | Age specific failure probability |
| $f_{C,i}$ | Customer category-specific impact factor |
| $f_m(X)$ | Objective function |
| $F(t)$ | Cumulative distribution function |
| $g$ | Index of groups |
| $h$ | Hazard |
| $\hat{h}_i$ | Empirical hazard |
| $\widehat{h1}_i$ | Empirical hazard function 1 |
| $\widehat{h2}_i$ | Empirical hazard function 2 |
| $i, j$ | Index of pipe |
| $instD_i$ | Installed date of each pipe $i$ |
| $Ic_{i,t}^{tot}$ | Total service interruption impact of each replacement pipe $i$ |
| $Ic_i^{tot}$ | Total impact of customer interruption for each pipe $i$, at each year $t$ |
| $Ic_{rep,i}$ | Service interruption impact of each replacement pipe $i$ |
| $Ic^{tot}$ | Total service interruption impact for the whole network |
| $I[i]_{distance}$ | Crowding distance for individual $i$ |
| **J** | Judgment matrix |
| $I_i$ | Time intervals |
| $l_i$ | Length of the pipe $i$ |
| $L_i, R_i$ | Truncated time interval |
| $m$ | Number of objective functions |
| $M_i$ | Machinery for replacing pipe $i$ |
| $M_{ij}$ | Machinery for replacing pipe $i$ and pipe $j$ |
| $n$ | Total number of pipes in the network |

| | |
|---|---|
| $n^*$ | Sample size |
| $N(t_i)$ | The numbers of components, which are functional at time $t_i$ |
| $N_{LR}$ | Length of pipes repaired in the time interval $(L_i, R_i)$ |
| $N_{LR}(t_i)$ | New repaired length at time $t_i$ |
| $Nseg$ | Number of segments of pipe |
| $NOG$ | Number of groups for the whole system |
| $NOP_g$ | Number of pipes in each group $g$ |
| $NOP^*$ | Maximum number of pipe in one group |
| $N_{c,i}$ | Number of customers interrupted by replacing pipe *i* |
| $N_{c,i,j}$ | Overlap number of customers interrupted by replacing pipe *I* and pipe *j* |
| $P_c$ | Probability of crossover |
| $PV^{tot}$ | Total system net present value for pipes replacement |
| $PV_{i,t}^{tot}$ | Net present value of total cost of replacing pipe *i* at its calendar year *t*, during the planning horizon *T* |
| $PV_{fail,i,t}^{tot}$ | Net present value of total repair cost of replacing pipe *i* at its calendar year *t*, during the planning horizon *T* |
| $PV_{repl,i,t}^{tot}$ | Net present value of total replacement cost of replacing pipe *i* at its calendar year *t*, during the planning horizon *T* |
| $r$ | Social discount |
| $r_i$ | Number of components at risk at $t_i$ |
| $R_h$ | Mean value of the residual for the true hazard and fitted hazard |
| $R_{fail}$ | Failure cost rate |
| $R_{repl}$ | Placement cost rate |
| $S_g$ | Judgment value |
| $t_i$ | Instant time, $i = 1,2,\cdots$ |
| ${t_g}^*$ | New replacement year for each pipe in group *g* |

| | |
|---|---|
| $T$ | Planning period |
| $\mathbf{x}^{(L)}$ | Lower bounds for each individual |
| $\mathbf{x}^{(U)}$ | Upper bounds for each individual |
| $x_{ig}$ | Judgment value |
| $\boldsymbol{X}$ | Explanatory variables of regression tree |
| $\boldsymbol{Y}$ | Response variables of regression tree |

*Greek Letters*

| | |
|---|---|
| $\alpha$ | Scale parameter of a Weibull distribution |
| $\beta$ | Shape parameter of a Weibull distribution |
| $\varepsilon_{ij}$ | Values in the Judgement matrix |
| $\varepsilon_{ij}^{GD}$ | Group scheduling factor of the shortest geographic distance |
| $\varepsilon_{ij}^{EU}$ | Group scheduling factor of the maximum replacement equipment utilization |
| $\varepsilon_{ij}^{CI}$ | Group scheduling factor of the minimum service interruption |
| $\lambda$ | Constant failure rate |
| $\mu_{rep}$ | Mean cost value for each repair |
| $\sigma_{rep}$ | Standard deviation of the repair cost |
| $\xi$ $(tw)$ | Start time of Phase III (wear-out point) |
| $\tau$ | Age of pipe |
| $\tau_{best}$ | Optimal time interval for replacement |
| $\gamma_{ij}$ | Geographic distance from pipe *i* to pipe *j* |
| $\gamma^{*}$ | User-defined maximum geographic distance |
| $\varphi$ | A parameter for indicating the impact of service interrupted duration |

# Statement of Original Authorship

The work contained in this thesis has not been previously submitted to meet requirements for an award at this or any other higher education institution. To the best of my knowledge and belief, the thesis contains no material previously published or written by another person except where due reference is made.

QUT Verified Signature

Signature:

Date: 10/01/2014

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# Chapter 1: Introduction

## 1.1 INTRODUCTION OF RESEARCH

The management of water pipelines can present particular challenges. A water pipeline belongs to a class of assets known as linear assets, similar to a road, a rail track, electricity power line, a gas and oil pipeline or a telecommunications network. Pipelines in underground water distribution systems deteriorate over time. This deterioration of water pipelines leads to failures such as leaks and breakage, which in turn cause loss of valuable water, urgent and unscheduled maintenance activities, interruption of water supply, even property damages or loss of life. Some of these consequences tend to be interrelated and can compound leading to highly expensive scenarios.

Most water pipelines were constructed several decades ago, and some of the construction dates can be traced back to the 1900s, especially in developed countries. As water pipelines deteriorate, failures may occur frequently. For example, hundreds of breaks occur in North America each day, and people in North America have suffered well over a million cases of broken water pipelines over the last 10 years, costing around $US 40 billion in maintenance [1].

The American Water Works Association (AWWA) predicted that more than one million miles of water pipelines were nearing the end of their useful life and approaching the age at which they need to be replaced [2], such that replacement costs combined with projected expansion costs will cost more than one trillion USD over the next few decades [3].

Consequently, cost-effective and economical-friendly replacement or renewal of water pipelines has become the major concern of many operators of water utilities. However, cost-effective replacement scheduling is difficult, because (1) pipelines are usually buried underground and hard to access; (2) they often have different ages, construction methods and technical specifications; (3) they can cross jurisdictional borders; and (4) their replacement often causes service interruptions to customers.

Scheduling replacement of water pipelines would not be a problem if there were unlimited resources in time, workforces, budgets and equipment. However, resources are always scarce and thus decisions must be made regularly to meet multiple key criteria. This requirement pressures utility managers, who have to develop optimal replacement schedules in order to maximise investment return and provide acceptable, high quality water supply services.

Utility managers often face immense challenges when making decisions about scheduling replacement of water pipelines. Their major concerns are to determine which pipeline needs to be replaced and when is the optimal time to replace. For instance, if utilities delay the replacement of deteriorated pipelines, failures of pipelines will happen, which usually impacts society adversely. If utilities replace the deteriorated pipelines prematurely, it would lead to unnecessary expense for water utilities and service interruptions to customers. Therefore, it would be advantageous to optimise the schedules for replacement, considering multiple objectives, such as optimising system availability [4, 5], costs [6-8] and system performance [9, 10].

In practice, replacement of water pipelines is usually scheduled into groups based on expert experiences. This activity is termed 'group replacement schedules' in this research. Multiple pipelines are selected to group one replacement job in order to improve replacement efficiency, so as to reduce maintenance costs. After conducting an extensive literature review, several limitations of existing models have been identified.

(1) Much of the existing research [6, 8, 11, 12] focuses on analysing scheduling optimisation for individual/single pipelines, where optimal replacement time (usually in years) can be scheduled for each single pipeline. The practical needs for optimising group replacement schedules of pipelines cannot be met by simply applying current optimisation and hazard modelling methodologies from the existing body of knowledge. Methodologies for optimising group replacement schedules of water pipelines have not been reported in the literature.

(2) Reliability prediction is essential for optimising replacement schedules. Existing reliability models often consider the entirety of the water pipes rather than the individual contributions of different components of the water pipes. Moreover, they cannot take into account of the multiple failure characteristics and mixed failure distributions, and deal with complex censorship pattern of lifetime data.

In this thesis, the candidate described the development of new models and methodologies for optimising the replacement schedules for water pipelines. In this chapter, the objectives of the research program and the research methods will be surveyed. The detailed research question will be described followed by each objective. The outcomes of this research and the relationship among the developed models will be summarised. The original contributions made by the candidate will also be identified.

## 1.2 RESEARCH OBJECTIVES

The overall research objective in this thesis is to develop new models and methodologies for optimising group replacement schedules of water pipelines. The goal is to improve the efficiency of replacement, hence to reduce total system costs and service interruptions. The detailed objectives of the candidature are as follows:

**(1) Development of a new multi-objective optimization model for group replacement schedules of water pipelines**

The first objective of this candidature is to develop a new model for optimising group replacement schedules of water pipelines for multiple objectives. This new model is able to extend the previous research in three ways:

(a) Considering multiple criteria for replacement scheduling

Replacement activities are usually scheduled in groups manually, based on expert experience case-by-case. This practice fails to provide an optimal solution, because optimised replacement schedules cannot be derived by expert experience only. Optimising group replacement schedules of water pipelines needs to take into consideration multiple criteria, such as costs, impact of service interruptions, pipe specifications, the type of technology employed and geographical information. It appears that replacement scheduling considering multiple criteria has not received enough attention in literature to date. This candidature addresses these issues and proposes a method to model multiple criteria for optimising group replacement schedules of water pipelines.

(b) Considering groups of pipelines in cost and service interruption models

It appears that most previous cost models and service interruption models for replacement of water pipelines were developed for individual water pipes, which cannot be applied for group scheduling. Replacement of groups of pipelines needs to calculate the costs savings and reduction of service interruptions. Therefore, this candidature has proposed a new cost model and a new customer interruption model for optimising group replacement schedules, which take into consideration of costs savings and reduction of service interruptions.

(c) Considering allocation of pipelines in optimisation algorithm

Optimising group replacement schedules of water pipelines is complex due to various decision variables, which could be in both time and space domains. Existing optimisation algorithms applied in replacement schedules cannot be applied directly to deliver optimal solutions, for the reason that they are unable to consider pipe allocation into the algorithms, so they can only optimise replacement schedules for single pipes rather than groups of pipes. Therefore, a modified optimisation algorithm based on an existing multi-objective optimisation algorithm is necessary to be developed to deal with the pipe allocation issue.

In this candidature, a multi-objective replacement decision optimisation model for group scheduling (RDOM-GS) was developed. The proposed research therefore significantly advances the knowledge in replacement schedule optimisation for group of water pipelines.

**(2) Development of a hazard-based modelling method for reliability analysis of water pipelines**

In order to derive optimal replacement time for groups of pipelines, reliability prediction analysis is essential in this research. A discrete hazard modelling method [13] has been developed for modelling reliability of linear assets. However, this model has several limitations. For example, it assumes that all pipes have the similar failure characteristics, and therefore this method use single failure distribution for different water pipelines. Moreover, failure data of water pipelines are truncated and existing models do not deal with this truncation sufficiently. Therefore, the second objective of this candidature is to develop an improved hazard-based modelling method for water pipelines. This new method addresses these deficiencies in three ways:

(a) Statistical grouping analysis for reliability prediction

One of fundamental limitations for applying existing hazard models is the requirement of statistical grouping to partition pipe data based on their specific features. Previous approaches in the literature appear to partition water pipes into groups on an ad hoc basis. Grouping criteria need to be decided at first based on prior knowledge, followed by validation based on the pre-determined criteria. However, prior knowledge of grouping criteria is unable to balance the number of groups as well as the need of sufficient sample size in each group. Moreover, previous approaches assumed that the breakage rate followed by exponential increases, which is not in accord with reality for water pipelines, for instance, pipes may have distinctive breakage rate patterns for different ages. Therefore, there is a requirement of developing an effective approach of statistical grouping to improve reliability analysis for water pipelines.

(b) Critical evaluation of two commonly used empirical hazard formulas

Through literature review, two empirical hazard formulas can be derived from the theoretical hazard function[14-16]. However, previous research did not investigate the differences between the two formulas in terms of derivations and applications. These differences may result in deviations of calculating the empirical hazard. Therefore, evaluation of the two formulas is essential to choose an appropriate one for reliability analysis of water pipelines.

(c) Empirical hazard function to deal with truncated lifetime data

Maintenance histories are typically available for a relatively short and recent period, often less than a decade. The irregular, non-random distribution of pipe installations combined with the short observation period of failures often produce a complex censorship pattern, which is not amenable to treatment by existing hazard models in previous research. This complex censorship pattern may result in underestimation of hazard calculation. Therefore, an empirical hazard model that considers complex censorship pattern of lifetime data is required to effectively reduce the underestimation effects.

During this research, an improved hazard-based modelling method for water pipelines has been developed to account in multiple failure characteristics and truncated lifetime data. This candidature therefore significantly advances the knowledge in hazard modelling of water pipelines for reliability prediction analysis.

**(3) Verification of models/methodologies**

The third objective of this candidature is to verify the above models and methodologies using appropriate experimental analysis methods. The verification includes designing and conducting numerical simulation experiments based on real data from industry. The data includes failure time, failure modes, working hours, repair and replacement cost, number of customers, impact factor for service interruption, geographical information for each asset, general information for each asset, e.g. length, material, diameter.

The above-proposed models/methodologies deal with the identified limitations in previous research. Objective (1) focuses on the optimisation of group replacement schedules of water pipelines based on multiple objectives and multiple group scheduling criteria. Objective (2) concentrates on the reliability prediction of water pipelines to deal with multiple failure characteristics, mixed failure distributions, and truncated lifetime data. The prediction outputs of Objective (2) are integrated with Objective (1) to deliver optimised group replacement schedules of water pipelines.

## 1.3 RESEARCH METHODS

To achieve these objectives, both theoretical modelling methodologies and experimental analysis were used. The entire candidature was divided into two stages. In Stage 1, an improved hazard-based modelling method was developed for r predicting the reliability of water pipes. This method is able to handle the features of real water pipelines data, having multiple failure characteristics and mixed failure distributions, as well as short observation period of lifetime data. The improvements of this proposed method consist of three separate parts: a statistical grouping algorithm, an evaluation on two frequently used empirical hazard formulas, and a modified empirical hazard model for truncated lifetime data. In Stage 2, a multi-objective replacement decision optimisation model for group scheduling (RDOM-GS) was developed. RDOM-GS integrates the hazard prediction results in Stage 1. RDOM-GS contains three parts: (1) a modelling method for multi-criteria group scheduling, (2) cost and service interruption models, and (3) a modified non-dominated sorting genetic algorithm-II (NSGA-II). The relationship between Stage 1 and Stage 2 can be illustrated in Figure 1-1.

During these two stages of research, simulations, and industrial case studies were conducted to verify the developed models and methodologies. More details about the research methods are presented as follows:

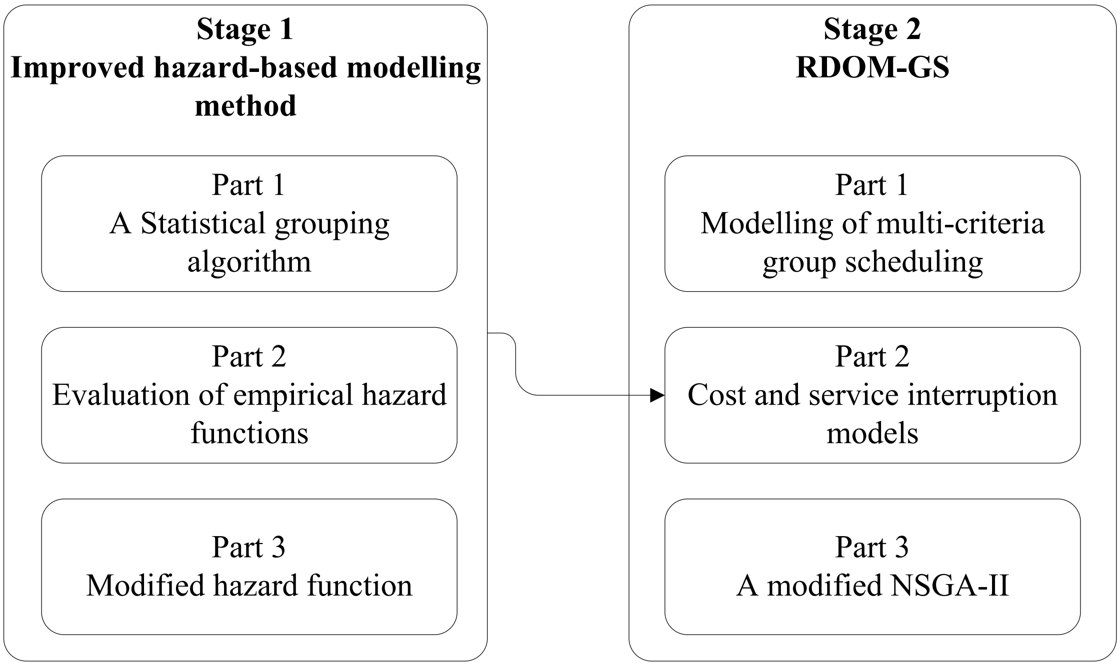


Figure 1-1 Stage 1 and Stage 2

**(1) Stage 1**

The candidature in this stage is related to the second objective of the research program, i.e., to develop an improved hazard-based modelling method to predict the reliability of water pipelines. This approach is used to explicitly predict the reliability of water pipelines taking into account real lifetime data.

To achieve this goal, an improved hazard modelling method for water pipes was developed based on a piece-wise hazard modelling method[13]. This new method consists of three separate parts:

The first part aims to develop a consistent and systematic statistical grouping algorithm for subsequent linear assets reliability analysis. The statistical grouping algorithm aims to partition water pipes into relatively more homogeneous subgroups, where the interactions among different features are more manageable.

This statistical grouping algorithm has a four-step procedure: (a) age specific material analysis, (b) length related pre-grouping, (c) regression tree analysis, and (d) criteria adjustment. This algorithm uses recursive partitioning to assess the effect of specific variables on pipe failures, thereby ultimately generating groups of pipes in terms of similar statistical features. Moreover, this algorithm balances two grouping conditions (a) homogeneity in each group, and (b) sufficient data in each group for hazard prediction.

The second part aims to evaluate the two frequently used empirical hazard formulas, to determine how the empirical hazard should be calculated. This candidature conducted both theoretical derivation and simulation experiments using simulation samples based on exponential and Weibull distributions in order to compare their estimation performances against the true hazard function values. This candidature also evaluated the relative differences of the calculated empirical hazards between these two formulas under practical situations.

The third part is to develop an empirical hazard function for truncated lifetime data. Truncated lifetime data causes the calculated empirical hazard to underestimate the true hazard. In this part, the empirical hazard function was modified to deal with the truncated lifetime data. The modified empirical hazard function treats water pipes as a number of unit-length pipe segments, and it takes observed pipe segments and replaced pipe segments into consideration in the truncated observation period.

**(2) Stage 2**

In the second stage of the candidature, a new model was developed to optimise group replacement schedules of pipelines, based on multi-objective, which is named as Replacement Decision Optimisation Model for Group Scheduling (RDOM-GS). The RDOM-GS can integrate the outputs of improved hazard model in Stage 1 to calculate the total costs and the total service interruption impacts. This new model improves existing optimisation approaches for group replacement schedules of water pipelines, by taking multiple group scheduling criteria into consideration. This model contains three parts:

**a) Modelling of multi-criteria group scheduling**

The first part is to model the group scheduling criteria. Three group-scheduling criteria were selected including minimum geographical distance, maximum replacement equipment utilisation and minimum service interruption. This candidature developed three models to calculate geographical distance, equipment utilisation and interrupted number of customers. The three grouping criteria are modelled based on a judgment matrix to quantify the values of group scheduling.

**b) Cost and service interruption models**

The second part aims to develop a cost model and a service interruption model for optimising group replacement schedules of water pipelines. The formulas of repair cost, replacement cost, total cost, and total service interruption are developed for groups of pipelines based on pipe length, diameter, material, historical cost data, and the hazard prediction results calculated using the improved hazard model developed in Stage 1. These formulas enable RDOM-GS to integrate cost analysis and service interruption analysis into optimising replacement schedules.

**c) A modified non-dominated sorting genetic algorithm-II (NSGA-II)**

The third part aims to develop a modified NSGA-II. This candidature proposed a newly designed encoding method, a modified mutation operator, and a modified crowding distance calculation method. These modifications take into account the complexity of optimising group replacement schedules of water pipelines, and considering the allocation of pipelines in the optimisation algorithm.

**(3) Validation of Methodologies and Models**

The newly developed models/methodologies have been verified using both experimental data from numerical simulation and the real-world data from industry.

The verification of the hazard modelling method was mainly conducted using simulation experiment and maintenance data from industry. A Monte Carlo simulation framework is developed to alleviate the problems of short observation period and complex censorship patterns of real lifetime data of water pipes. The core simulation unit generates synthetic failure data, which displays realistic censorship patterns as observed in real-world data, providing a controlled test bed for the development and evaluation of failure models. The inputs of the simulation framework include: (1) a collection of linear asset descriptors; (2) the distribution of failure times; and (3) the start-and-end dates of the simulated record keeping period.

The verification of the RDOM-GS was conducted using field data from industry. The field data included the repair records of water pipelines, general information on water pipes, e.g. length, diameter, material, geographical information, data related to service interruption, and cost data. The Corporative Research Centre (CRC) on Infrastructure and Engineering Asset Management (CIEAM) provided partial funding to support the data collection phases for this candidature.

The raw data was analysed through a pre-analysis to filter out those invalid data. All pipes were partitioned into a number of groups using the statistical grouping algorithm. For each group, the empirical hazard was calculated using the modified empirical hazard function for truncated lifetime data. Repair cost history records were analysed using non-linear regression to estimate the repair cost. Then, RDOM-GS was applied to optimise the replacement decision based on group scheduling. Finally, the outputs of RDOM-GS include (1) a Pareto-optimal set and (2) the scheduled replacement activities for each calendar year with the information on a water pipe's unique ID, total cost and total service interruption.

## 1.4 OUTCOMES OF THE RESEARCH

The candidature in this thesis explored two new research areas – (1) the research on optimisation of group replacement schedules considering multiple criteria, and (2) prediction of water pipelines reliability, considering multiple failure characteristics, a mixture of failure distribution, and truncated lifetime data. The research composed mathematical modelling and theoretical analysis, as well as validation of the developed models using numerical simulation, and life data from industry.

The important outcomes of the work in this thesis are as follows:

**(1) An optimization model for group replacement schedules of water pipelines – RDOM-GS**

The RDOM-GS is linked the first objective of the research program. RDOM-GS models the group replacement schedules of pipelines with multiple objectives, minimising total system costs, and minimising total system service interruption impacts. RDOM-GS takes into consideration multiple group scheduling criteria, shortest geographic distance, maximum machinery utilisation, and minimum service interruption. The new cost model categorising replacement costs into length-related cost, machinery cost and transportation cost is developed for group scheduling. The model for service interruption calculates the number of customers impacted, due to groups of replacement activities. This multi-objective and multi-criteria optimisation model, RDOM-GS, can be applied to other linear assets, such as road, railway, and electricity cable networks.

**(2) A modified NSGA-II**

This candidature has developed a modified NSGA-II to deal with the challenges of pipelines allocation for optimisation of group replacement scheduling of pipelines, which enables the RDOM-GS to deliver replacement schedules in order to minimize total life-cycle cost at a specified service interruption level. The new encoding method considers both time domain (replacement year) and space domain (pipes allocation) of group scheduling, which makes the scheduling optimisation of groups of pipelines applicable. The modified mutation operator and crowding distance calculation method ensure that the NSGA-II has a better convergence to the Pareto-optimal set and the better diversity in the solutions of the Pareto-optimal set.

**(3) An improved hazard-based modelling method**

This candidature has developed an improved hazard-based modelling method, which include three consistent parts:

The first part - the statistical grouping algorithm, is able to divide pipes into different feature groups for hazard modelling. This statistical grouping algorithm can systematically partition pipes into statistical groups based on pipes' different features, as well as keeping a sufficient sample size in each group. No prior knowledge for deciding pre-determined groups is required.

The second part - evaluation of two seemingly identical empirical hazard formulas, improves the confidence of empirical hazard calculation. The candidate concluded that the formula, which calculates the average failure rates, gives less biased estimation than the other one in all cases. This candidature also provided a rule for applying the two formulas with their application conditions and estimation accuracy.

The third part - a modified empirical hazard function, deals with truncated lifetime data. This modified empirical hazard function can effectively reduce the underestimation effects by considering the survived pipe segments within the observation period combined with the new pipe segments.

**(4) Validated the newly developed methodologies and models using Monte Carlo simulation and the data collected from industries**

This work included designing and implementing simulation experiments, as well as collecting and handling life data.

This candidature proposed a Monte Carlo simulation framework to support hazard modelling of water pipelines. It is able to alleviate the problems of complex censorship patterns of lifetime data caused by non-random distribution of pipe installations combined with the narrow band of observed failures.

The candidate conducted a real case study from a water utility by applying the proposed models and methodologies in this candidature. The results illustrated significant reductions of total costs and service interruption. Approximately 5% total savings on replacement cost and 11.25% decreases in total number of customers interrupted can be expected for group replacement schedules if applying the proposed RDOM-GS.

## 1.5 ORIGINALITY AND INNOVATION

Compared with existing research, this candidature has a number of innovations:

The proposed multi-objective RDOM-GS is the first model that can be systematically applied to schedule groups of replacement activities of water pipelines. This new model is expected to effectively reduce the total system costs and service interruption impacts for replacing water pipelines. This candidate has made the following original innovations:

(1) Multiple group scheduling criteria were modelled in RDOM-GS, e.g. shortest geographic distance, maximum machinery utilisation, and minimum service

interruption. The group replacement schedules were modelled based on the judgment matrix to determine the mode of pipes' combination.

(2) The new replacement cost model for scheduling groups of pipelines considers replacement cost as a combination of length related cost, machinery cost and transportation cost. The cost saving of scheduling groups of pipes can be calculated, which is more suitable for reflecting the real situation of replacement costs.

(3) A new service interruption model for group replacement scheduling of pipelines is able to calculate the service interruption impacts rather than equivalent interruption cost. The reduction of service interruption by replacing groups of pipes can be calculated through this model, by calculating the interactive number of customers interrupted in each replacement group.

This candidature developed a modified NSGA-II to deal with multiple objective optimisation problems for group replacement scheduling of water pipelines, which enables the RDOM-GS to deliver replacement schedules in order to minimize total life-cycle cost at a specified service interruption level. This candidate has made the following original innovations:

(1) A new encoding method to deal with both time domain and space domain using evolutionary algorithms. A two-layer structure has been introduced to consider time variable (replacement year) as well as pipe allocation (replacement group), which has not been found in existing encoding methods for replacement optimisation of water pipes.

(2) A modified mutation operator to change mutation probability dynamically and to keep replacement year in order.

(3) A modified crowding distance calculation method by considering the proportion of the fitness values between two individuals to improve the diversity in the solutions of the Pareto-optimal set.

This candidature has developed the improved hazard based modelling method to predict the reliability of water pipelines. It has been able to effectively overcome the limitations by applying an existing hazard model [13]. I can meet the following three requirements for hazard modelling of water pipelines: the requirement for partitioning pipes into relatively homogeneous groups based on specific features of water pipelines, the requirement for dealing with underestimation effects caused by truncated lifetime data, and the requirement for evaluating two frequently used empirical hazard formulas. Three innovative components have been developed, which include a statistical grouping algorithm for reliability analysis, an empirical hazard model to deal with the underestimation effects of true hazard, based on real life data, and an evaluation on application impacts for two empirical hazard formulas.

Generally, the proposed improved hazard modelling method has the following major advantages:

(1) Ability to systematically partition pipe data into different statistical groups based on pipe's features, e.g. length, diameter, material. The four-step procedure in the statistical grouping algorithm is able to partition pipe data into more relatively homogeneous groups and at the same time, keeps a sufficient sample size of failure data for reliability analysis in each group. No distribution assumptions and prior knowledge are required for the proposed statistical grouping algorithm.

(2) Ability to reduce the underestimation effects caused by real life data. Field lifetime data for water pipes normally contain a great proportion of truncated data with a complex censorship pattern, which results in the underestimation of the true hazard by applying existing empirical hazard models. The modified empirical hazard model proposed in this research is able to reduce the underestimation effects by considering the survived pipe segments within the observation period, and the new, repaired pipe segments.

(3) Ability to differentiate the application impacts of two commonly used empirical hazard formulas. This candidature proposed the first comparative study of the two empirical hazard formulas based on theoretical analysis and simulation experiments. It provided a rule-of-thumb using these two formulas for hazard modelling, which has not been found in the literature.

(4) The proposed Monte Carlo simulation framework of water pipes is able to generate test-bed sample data sets in terms of the main features of the real data of water utility. This framework can be used to evaluate algorithms for heavily

censored data, measure impact of censorship on model accuracy, and assess accuracy and robustness of model fitting algorithms.

The new methodologies and models developed in this candidature are expected to enrich the knowledge of optimisation for group replacement schedules and hazard modelling through effectively addressing some significant limitations of existing models. The research outcomes are of significance for maintenance decision support for water pipelines. A number of new methodologies and models developed in this candidature have been chosen for use in a software tool, LinEAR, and will become one of the unique features of this advanced software.

The new methodologies and models developed in this candidature are in the context of water pipelines, but it is domain-independent and therefore it has potential to be applied to other linear assets, e.g. rail and electricity cable networks.

Due to the innovative and significant outcomes from this candidature, this candidate has won the Award of Early Career Researcher 2012 from the Cooperative Research Centres (CRC) Association of Australia. This national award is presented annually to only one student throughout Australia.

## 1.6 RESEARCH PROCEDURES

This candidature can be divided into four major components as shown in Figure 1-2. The first component is to develop an improved hazard-based modelling method for water pipes. It includes four consistent parts: a statistical grouping algorithm based on a regression tree, a comparative study for two empirical hazard formulas, an empirical hazard function for truncated lifetime data for linear assets, a Monte Carlo simulation framework for generating test-bed samples considering the main features of the real-world data.

The second component of this candidature is a multi-objective replacement optimisation model for group scheduling (RDOM-GS). This model contains the development of group scheduling criteria, a judgment matrix, cost model and service interruption model. The cost model and the service interruption model can be integrated with the outputs of the improved hazard model in first component.

The third component of this candidature focuses on the multi-objective optimisation algorithms for replacement group scheduling optimisation. A modified NSGA-II was developed with a number of modified operators of genetic algorithms.

The last component of this candidature validates the proposed methodologies and models based on a real case study from a water utility, which includes data pre-analysis, grouping analysis, hazard modelling and prediction, application of RDOM-GS and results discussion.

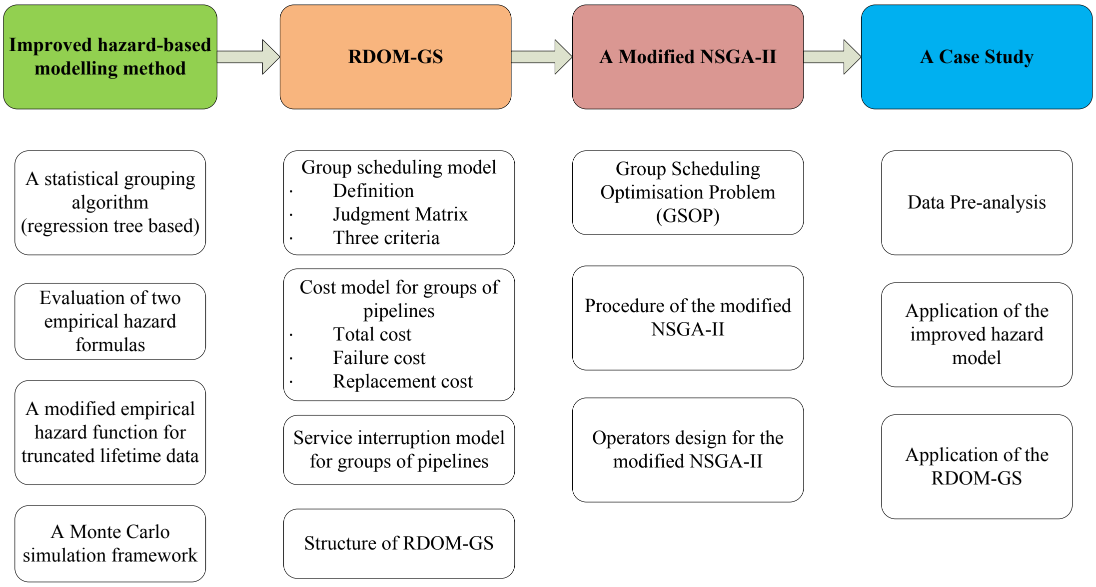



Figure 1-2 Research procedures

## 1.7 PUBLICATIONS GENERATED FROM THIS RESEARCH

Li, Fengfeng, Ma, L., Sun, Y., and Mathew, J. “Replacement Decision Optimization Model for Group Scheduling of Water Pipeline Network.” Journal of Water Resources and Management, submitted.

Li, F., et al. (2014). Group Maintenance Scheduling: A Case Study for a Pipeline Network. Engineering Asset Management 2011. J. Lee, J. Ni, J. Sarangapani and J. Mathew, Springer London: 163-177.

Li, Fengfeng, Sun, Y., Ma, L., and Mathew, J. "A Grouping Model for Distributed Pipeline Assets Maintenance Decision." Proc., *The Proceedings of 2011 International Conference on Quality, Reliability, Risk, Maintenance, and Safety Engineering*. IEEE. 627-632.

Xie, G., Fengfeng Li, et al. Hazard Function, Failure Rate, and A Rule of Thumb for Calculating Empirical Hazard Function of Continuous-time Failure Data. *The 7th World Congress on Engineering Asset Management* (2012). Daejeon, Korea.

## 1.8 SOME IMPORTANT DEFINITIONS

Throughout this thesis, definitions of terms are given when they are introduced. However, definitions of some of the more important terms used in the reliability evaluation of engineering systems and maintenance decision support are collected in this section for easy access and reference.

*As bad as old*: if the condition of a repairable system after a repair is the same as it was just before the repair, the system is said to be in an "as bad as old" condition after the repair.

*Corrective maintenance*: in water network management, a strategy is corrective if action is taken after a failure has occurred.

*Covariate*: all those factors that have an influence on the reliability characteristics of a system are called covariates. Covariates are also called variables, explanatory variables or risk factors. Examples of covariates include environmental factors (e.g. soil condition), hydraulic factors (e.g. pressure) and structural variables (e.g. diameter)

*As good as new*: If the condition of a repairable system after a replacement is reset to that of a new system, the system is said to be in an "as good as new" condition after the replacement.

*Data grouping:* Failure records may contain distinctive distribution features in different groups, which can be identified with properly grouped pipes in terms of pipe length, diameter, material types, installation year and soil types. Data grouping is to partition pipes' data into more homogeneous groups, where the hazard curves between groups are clearly distinctive from each other.

*Group scheduling:* Given a water pipes' network of $N$ individual pipes with an inventory of their information, given a replacement-planning period of $T$ years, how the pipes or pipe segments should be scheduled into groups of replacement activities is based on multiple criteria to meet multiple objectives.

*Hazard/hazard rate:* Instantaneous failure rate.

*Lifetime*: The concept of lifetime applies only for components, which are discarded the first time they fail. The lifetime of a component is the time from when the component is put into function until the component fails.

*Pipe*: pipe is identified from one node in the water network to another (e.g. manhole, network junction). Each pipe normally consists of a number of “pipe segments”.

*Pipe segment*: the smallest unit of pipe, which is linked one-by-one through welding process or flange. The pipe segment is determined by the standard construction of pipe.

*Pipeline*: pipeline contains a number of pipes connected with joints and valves. It is a general statement of a number of water pipes. Pipeline replacement means replacement activities conducted at a number of specific pipes.

*Proactive maintenance*: In water network management, a strategy is proactive if a maintenance action is taken before a failure occurs.

*Rehabilitation*: All methods for restoring or upgrading the performance of an existing pipeline system. The term rehabilitation includes repair, renovation, renewal and replacement.

*Renewal*: Construction of a new pipe, which fulfils the same function in the distribution system but does not necessarily have an identical path to the pipe it is replacing.

*Renewal process*: A failure process for which the times between successive failures are independent and identically distributed with an arbitrary distribution. When a component fails, it is replaced by a new component of the same type, or restored to “as good as new” condition. When this component fails, it is again replaced, and so on.

*Renovation*: Methods of rehabilitation in which all or part of the original fabric of a pipeline are incorporated and its current performance improved. Relining is a typical example of pipe renovation.

*Repair*: An unplanned maintenance activity carried out after the occurrence of a failure. After the repair, the system is restored to a state in which it can perform a required function (e.g. supplying water). (Rectification of local damage)

*Replacement*: Construction of a new pipe, on or off the line of an existing pipe. The function of the pipe will incorporate that of the old, but may also include improvements.

*Water pipe failure*: break or leakage on a pipe.

*Water main*: a principal supply pipe in an arrangement of pipes for distributing water in water pipe network.

## 1.9 THESIS OUTLINE

The thesis is primarily composed of seven chapters.

**Chapter 1 Introduction**

The topic and the scope of the research program are presented. The objectives of the research program and the methods used to achieve the research objectives are described. The outcomes of the research and the innovative contributions made by the candidate are identified.

The rest of this thesis is organised as follows:

**Chapter 2 Literature Review**

The literature review of this thesis consists of four parts corresponding to the identified research objectives. The first part reviews the significance of the water pipe failures followed by the discussion of the causes of failures of water pipelines. The second part focuses on statistical modelling for pipeline failures. The limitations and advantages of these models are discussed and summarised as well. The third part reviews the decision support method and models for water pipeline replacement optimisation, followed by the methodologies of multi-objective optimisation at the end of this chapter.

**Chapter 3 Am Improved Hazard-based Modelling Method for Water Pipelines**

In this chapter, an improved hazard-based modelling method for reliability analysis of water pipelines is developed. An introduction of linear assets is discussed, followed by an introduction of the piecewise hazard model for linear assets. Moreover, a statistical grouping algorithm, which partitions all water pipes into relatively more homogeneous groups, is developed, followed by a comparison study of two empirical hazard formulas. Furthermore, an empirical hazard model to deal with truncated lifetime data and a hazard distribution fitting method is developed, followed by a validation based on test-bed sample data sets generated by Monte Carlo simulation. The procedure of the improved hazard model for linear assets is summarised at the end of this chapter.

**Chapter 4 A Replacement Decision Optimisation Model for Group Scheduling**

This chapter proposes a multi-objective replacement decision optimisation model for group scheduling (RDOM-GS), which starts at the maintenance decision support on water pipe with the economics of repair and replacement. Then, cost functions for water pipe repair and replacement were introduced and developed, based on the improved hazard model developed in Chapter 3. Group replacement scheduling was discussed, and a judgment matrix and three integrated models for replacement group scheduling were developed. A new replacement cost function for group scheduling was developed, followed by the model for dealing with the customer service interruption. The objectives and constrains for RDOM-GS was summarized, followed by an introduction of the structure of the RDOM-GS.

**Chapter 5 An Improved Multi-objective Optimisation Algorithm for Group Scheduling**

This chapter proposes an improved multi-objective optimisation algorithm for replacement group scheduling optimistion problem (GSOP). It starts with a mathematical description of the GSOP followed by the analysis of its computational complexity. A modified NSGA-II to deal with GSOP was introduced, which includes a procedure and the operators. A comparison study for the modified NSGA-II and original NSGA-II based on two simplified objective functions was conducted at the end of this chapter.

**Chapter 6 Case Study from a Water Utility**

In this chapter, a case study was conducted using the data collected from a water utility to validate the proposed models. The chapter begins with a data pre-analysis, then a grouping analysis, hazard prediction, application of RDOM-GS and finally, results comparison.

**Chapter 7 Conclusions and Future Works**

The last chapter concludes the thesis and summarises the contributions and work of this candidature. Some possible research directions are also identified. These research directions can be pursued in the future as an extension of this candidature.

Throughout this study, a mathematic software tool MATLAB is used in most of the statistical analysis, and optimisation analysis. The software package Microsoft Access 2007 is used for raw data processing.

# Chapter 2: Literature Review

This chapter includes the review of literature on water pipe failures; statistical modelling methods for reliability analysis of pipe failures; methods and models of maintenance decision-making for water pipes; multi-objective optimisation methods. The research gaps are discussed in the last section.

## 2.1 WATER PIPE FAILURES

### 2.1.1 Consequences of water pipe failures

Water pipe is a type of infrastructure asset. When the pipe fails, the consequences may include loss of water, urgent and unscheduled maintenance activities, interruption of service, system performance decrease, consumer dissatisfaction, property damage, inefficient use of funds, and even catastrophic consequences. Some of these consequences tend to be either interrelated, or interact with each other, leading to more expensive scenarios. For example, loss of water service to commercial sites, which depend largely on water for servicing their customers, would lead to business loss. In some cases, undetected failed water pipes may create sinkholes by washing away the bedding underneath roads, which poses a hazard to both vehicular and pedestrian traffic.

With the aging of the water pipes, failures have been occurring with increasing frequency in recent years. According to a record [1], approximately 850 water main breaks have occurred in North America each day. Since January 2000, 4,019,274 broken water mains in North America have been recorded, and the costs are estimated around $US 40 billion, not including the high costs of emergency equipment, depleted water supply, traffic disruptions, and lost work time. Some of the water pipe failures can lead to severe disasters such as causing the interruption of water services, blocking road, and polluting the environment.

The situation for Australia is far from optimistic. Between 2009 and 2010, Adelaide recorded 22.4 failures per 100 km of pipe length, compared with 28.4 in Sydney, 37 in Brisbane and as much as 50 in Melbourne, according to the records from the

Water Services Association of Australia (WSAA)[17]. Some real examples of water pipe failures in Australia from the middle of 2010 to 2012 can be found in literature.

A water pipe ruptured in Brisbane's CBD on June 17th, 2010, leaving a large tear in the road and sending water gushing past alarmed pedestrians [18]. Two burst water mains led to a water shortage in Brisbane's north eastern suburbs on September 10th, 2011, and bottled water had to be supplied to the public for those suburbs [19]. A water main in Adelaide burst, flooding one car park on January 2nd, 2012, spilling into side streets and along footpaths [20]. Traffic in the morning peak was disrupted by a burst water main in central Adelaide on May 17th, 2012, which left a deep hole in the road [21]. Water cascaded down a street in Sydney on July 3rd, 2012, when a water pipe burst, flooding up to 12 houses and causing a burst of a gas main, with a road and a driveway upended and torn apart [22]. A number of months later, on October 29th, 2012, a water main burst in Glen Waverley, in Melbourne's eastern suburbs; up to 2 million litres of water were lost in the rupture as water shot up to 50 metres into the air for about an hour in the residential suburb. More than 100,000 homes were affected by the rupturing. A house suffered water damage, and a metal cage covering the main's pressure release valve was blown off and landed about 15 metres away, damaging the roof of a carport. The burst pipe was about 50 years old and had no history of failure [23].

### 2.1.2 Failure modes of water pipe

Water pipe failure is a general description of the water pipe’s state of not functioning, which includes a number of modes. WSAA [24] summarised the most common types of failure modes in water supply mains, which includes pieces blown out, perforation, broken back (circumferential break), longitudinal split, pipe wall rupture/tear associated with or during tapping, leaking joints, and third-party damage.

A number of factors influence the degradation of water pipes. The causes of water pipe failures can be classified into two major categories based on the physical degradation of water pipes, internal and external reasons. The factors, which were commonly assumed to have the greatest impact on pipe failure, include pipe’s age, installation period, corrosion, diameter, length, material, seasonal variation, soil condition, pressure, nearby excavation. [25].

A pipe’s structural variables, such as material, length and diameter, play a significant role on water pipe failure analysis. For example, according to a pipe’s structural ability, all materials can be classified with two categories, rigid material and flexible material. The rigid material pipes sustain applied loads by means of resistance against longitudinal and circumferential bending, while the flexible material pipes are pipes that deflect more than 2% of their diameter without any sign of structural failure. The categories of material for water pipes according to their structural ability are given in Table 2-1.

Table 2-1 Categories of water pipe material and abbreviations

<table>
<tr><th>Categories</th><th>Class</th><th>Material</th><th>Abbr.</th></tr>
<tr><td rowspan="10">Rigid</td><td rowspan="9">Concrete & Cement</td><td>Concrete</td><td>CONC</td></tr>
<tr><td>Reinforced Concrete Pipe</td><td>RCP</td></tr>
<tr><td>Steel Concrete Lined</td><td>SCL</td></tr>
<tr><td>Mild Steel Concrete Lined</td><td>MSCL</td></tr>
<tr><td>Asbestos Cement</td><td>AC</td></tr>
<tr><td>Vitrified Clay</td><td>VC</td></tr>
<tr><td>Fibre Reinforced Cement</td><td>FRC</td></tr>
<tr><td>Cast Iron Cement Lined</td><td>CICL</td></tr>
<tr><td>Ductile Iron Cement Lined</td><td>DICL</td></tr>
<tr><td rowspan="7">Metal</td><td>Cast Iron</td><td>CI</td></tr>
<tr><td rowspan="14">Flexible</td><td>Assumed Copper</td><td>ECOP</td></tr>
<tr><td>Copper</td><td>CU</td></tr>
<tr><td>Galvanized Wrought Iron</td><td>GWI</td></tr>
<tr><td>Steel</td><td>STEEL</td></tr>
<tr><td>Galvanised Steel</td><td>GAL</td></tr>
<tr><td>Mild Steel</td><td>MSCL</td></tr>
<tr><td rowspan="8">Plastic</td><td>Glass Reinforced Plastic</td><td>GRP</td></tr>
<tr><td>Poly Vinyl Chloride</td><td>PVC</td></tr>
<tr><td>Modified PVC</td><td>MPVC</td></tr>
<tr><td>Unplasticised Poly Vinyl Chloride</td><td>UPVC</td></tr>
<tr><td>Polyethylene</td><td>PE</td></tr>
<tr><td>High-Density Polyethylene</td><td>HDPE</td></tr>
<tr><td>Medium Density Polyethylene</td><td>MDPE</td></tr>
<tr><td>Fibre Reinforced polyester Pipe</td><td>FRP</td></tr>
</table>

Various types of material show different structural ability that lead to the differences of other factors that predominantly are the influence of pipe failures. For example, climate and clay soil conditions were the two critical factors for AC pipe failure [26], while the failure of UPVC pipes were more attributed to poor installation, excessive operating conditions, third-party damage or poorly manufactured solvent cement joints [27].

### 2.1.3 Replacement cost on water pipes

Due to the increasing trends of degradation and failures, maintenance of water pipes have become the major concerns of water utilities, particularly in the developed countries where a large number of water pipes have been established with a huge amount of previous investments.

Millette and Mavinic [28] indicated that Toronto city budgeted $US5 million in water distribution system repair due to corrosion in 1983, and the city of Winnipeg spent $US7.7 million for the same purpose. In the United States, the annual corrosion costs for maintenance of water pipelines are up to $US700 million, without the consideration of costs incurred for the repair of private water systems [28]. In Alaska, Alyeska maintained and operated the Trans-Alaskan Pipeline in 800 miles of pipeline from Alaska's North Slope oil fields to the port at Valdez. The project cost $US72 million [29]. Sydney Water awarded its Asia Pacific operation two contracts for small and medium diameter sewer and storm water pipeline rehabilitation. The combined three-year term contracts were lnsituform's largest award in Australia to date and had a budgeted value of $US27 million, with the potential for additional work [30]. The city of Durban in South Africa invested $US205 million to replace 1,750 km of ageing water pipe with trenchless technology. The new pipes have a fifty year lifespan and should significantly reduce the number of bursts, saving the municipality $US31.8 million per year [31]. In 2011, the Environmental Protection Agency of USA (EPA) invested $388,000 in the City of Russell, Kansas for improving its drinking water system. The purpose of the project was to replace old, deteriorating cast iron pipes with new plastic piping [32].

According to a record from the American Water Works Association (AWWA), more than one million miles of pipes are nearing the end of their useful life and approaching the age at which they need to be replaced [2], and these replacement costs combined with projected expansion costs will cost more than $US 1 trillion over the next two of decades [3].

All the investment schemes mentioned above have the objectives of improving drinking water systems and preventing water pipe failures thereby replacing old pipes with new ones. This leads to two research issues, (1) water pipe failure prediction based on statistical modelling, and (2) maintenance decision making for water pipes concerning how the replacement activities should be planned and scheduled taking into account multiple concerns.

## 2.2 RELIABILITY ANALYSIS FOR WATER PIPE NETWORKS

Reliability analysis plays a significant role in improving the performance of water pipe networks. System reliability is the probability that the system will perform its intended function for a specified interval of time under stated conditions [33].

A comprehensive review of the statistical models for structural deterioration of water mains before 2001 was conducted by Kleiner and Rajani[34]. They attempted to quantify the structural deterioration of water mains by analysing historical performance data. They classified the statistical methods into deterministic and probabilistic models. Their review provided descriptions of the various models including their governing equations, as well as critiques, comparisons and identification of the types of data that are required for implementation. Over recent years, a number of efforts were made to get better prediction results for water pipe failures.

A comparison study [35] for the log-linear ROCOF and the power law process using the maximized log-likelihoods was conducted to model the failure rate of the individual pipes. The study found that the log-linear ROCOF showed better performance than the power law process, when the 'failure-time-based' method was used. Recording each failure time resulted in better modelling of the failure rate than observing failure numbers in some time intervals. Wang and Zayed [36] developed a deterioration model which was applied to predict the annual break rates of water mains considering pipe material, diameter, age, and length based on five multiple regression models. This model analysed the deterioration trends of water mains, and it had limitations in interpreting the conditions of water mains. Fahmy and Moselhi[37] presented a failure forecasting model based on artificial neural networks (ANNs) to predict the remaining useful life of cast iron water mains, which was used to determine condition rating of the water mains. The model takes into account factors related to pipe properties, its operating conditions, and the external environment that surrounds the pipe. An ANNs based failure estimation model [38] was developed to predict the water mains failure and the determination of the benefit index for a city in the north of France. Six ANNs models were established on the basis of preliminary database analysis, which were constructed using a cross-validation approach. A framework of dynamic deterioration models[39] was developed combining individual prediction and group prediction. This model can avoid the uniform treatment of the entire sewer pipe network using the clustering and filtering process on the basis of location-related attributes and operational conditions. I-WARP [40] was developed based upon an non-homogeneous Poisson process (NHPP) to model breakage rates in individual water mains, which considered both static (e.g., pipe material, pipe size, age (vintage), soil type) and dynamic (e.g., climate, cathodic protection, pressure zone changes) factors.

When analysing the reliability of water pipes, existing models often consider the entirety of pipes in the pipe system. However, water pipes are typical linear assets; they do not have a clear physical boundary and usually span long distances, which can be divided into segments[41]. Each segment performs the same function but may be subject to different loads and environmental conditions. The failure of one pipe segment may not affect the reliability of other segments. Therefore, a water pipe should be treated as a number of segments. However, most of the existing models fail to consider the individual contributions of different segments of the pipe to the reliability of the system.

To deal with the segmentation issue in reliability analysis of water pipes, Sun et al. [13] proposed a piece-wise hazard model for linear assets. This model often experiences difficulty in analysing real lifetime data for water pipes. Failure records may contain distinctive distribution features in different groups, which can be identified through pipe length, size, material types, installation year, soil types, season. A fundamental issue for applying this model is the data grouping for reliability analysis [13]. Data grouping that aims to sub-divide the observation space into characteristically more homogeneous subgroups is necessary before reliability analysis.

Two questions need to be answered: what criteria should be used to form groups, and how many groups should be partitioned? The number of partitioned groups should balance two aspects: (1) homogeneity in each subgroup, and (2) enough failure data for hazard calculation. The more groups partitioned, the more homogeneous the characteristics within each group are, but fewer are the observations left in each subgroup for statistical analysis.

The literature provides a number of approaches to partition water pipe data into groups based on specific characteristics. Some categorize pipes based on engineering expert knowledge [42]. This type of approach has an advantage, in that grouping is based on practical experience for pipe characteristics and its failure modes. For instance, different materials have different physical characteristics, which may lead to different failure modes and failure rates. However, these methods only take materials and ages into consideration. An approach based on the one and two-way analysis of variance (ANOVA) has been developed [43] to analyse failure data. It groups data on breaks and establishes breakage rate patterns for each group. However, grouping criteria needs to be decided, first based on prior knowledge, before ANOVA to validate the grouping results. In general, prior knowledge of grouping criteria needs to be investigated. Moreover, it is assumed that the breakage rate is followed by an exponential increase over time, which in some cases is not in accord with the facts.

Therefore, a data grouping method needs to be developed, which can be used to analyse water pipe data, partition pipes into homogeneous groups, and simultaneously, keep sufficient sample size of failure data. Further literature review, specific to empirical hazard functions in reliability prediction models, is presented in the following chapters.

## 2.3 MAINTENANCE DECISION MAKING FOR WATER PIPE NETWORK

### 2.3.1 Maintenance strategy

Maintenance is considered as a key activity for water utilities to prevent water pipe failures and enhance network performance. It contributes to service with quality, and enriches all the company experience surrounding the service provided. In this section, the candidate has found references to three different types of maintenance strategies applied in distributed infrastructure network companies, including corrective maintenance, preventive maintenance, and predictive maintenance, which are described below:

Corrective maintenance (CM) can be defined as the maintenance that is required when an item has failed or worn out, to bring it back to working order. Corrective maintenance is carried out on all items where the consequences of failure or wearing out are not significant and the cost of this maintenance is not greater than preventative maintenance [44]. In current practice, maintenance providers often do corrective maintenance to a small range of pipe (some pipe segments, rather than all segments of the pipe) near a leak or rupture. This activity may consist of repair or restoration of pipes, and will be the result of a regular inspection, which identifies the failure in time for corrective maintenance.

Preventative maintenance (PM) is maintenance that is carried out to prevent an item failing or wearing out by providing systematic inspection, detection and prevention of incipient failure. Predictive Maintenance is often applied to aged pipelines to reduce unexpected failures and their resultant undesirable impacts. To improve the network reliability and prevent the failure from happening, maintenance people replaced particular old pipes with all new ones. Two commonly used PM policies include time based preventive maintenance (TBPM) and reliability based preventive maintenance (RBPM). In the TBPM policy, a pipeline is maintained based on scheduled PM times. The intervals between two PM actions may or may not be the same, whereas in the RBPM policy, a control limit of reliability is defined in advance. Whenever the reliability of a pipeline falls into this predefined control limit, the pipeline is preventively maintained. The purpose of PM is to improve the overall reliability of the entire pipeline[45]. Most maintenance of water pipe planning can be classified in RBPM.

In the predictive maintenance (PdM) technique, which is also referred to as a condition-based PM, the maintenance schedule and frequency match the age or health of the system at all times, making the schedule nearly optimum, prolonging the time to replacement (TTR) as a consequence. The expected times to future failure of a system are estimated during each operational period based on the variation pattern of its physical properties (condition monitoring) that are indicative of its state of degradation using implanted sensors, and the downtime schedule for each operation cycle is determined based on the estimated future failure times[46, 47]. For water pipes, condition assessment methods are essential for effective maintenance. A number of direct and indirect sensing techniques/technologies for inspection and detection of water pipe failures were developed in recent years, for example, CCTV, laser scan, electromagnetic methods, acoustic method, ultrasound methods. However, condition assessment for a water pipe system is costly: pipes tend to be hidden underground; they're hard to access; they're of different construction methods and specifications; they can cross jurisdictional borders; and they can be distributed in large geographical areas. In South-East Queensland, for example, one utility company is responsible for 8,744km of pipelines scattered in a geographical territory of 14,364 km². Therefore, the current relatively high cost of condition assessment technologies justifies their use mainly on large water transmission pipelines, where consequences of failure are relatively high. [48] The applications of assessment technologies were rarely used for the water supply industry, especially for some small water utilities.

### 2.3.2 Replacement decision making for water pipe network

Literature has shown numerous efforts in replacement decision making for water pipe network. Shamir and Howard[49] made the first attempt at determining the optimal time for water pipe replacement. Their model includes breakage rate data for each pipe and the present value costs of replacement and maintenance. It was a highly simplified approach, and many important elements were omitted in rehabilitation planning. Optimization techniques were regarded as the interaction of each water pipe with the network system as a whole. They considered both the performance and cost of the replaced system in the formulation of the replacement and renewal program. Based on that, a number of approaches had been reported, which contain the optimization of performance given a cost constraint [50] and the minimization of cost given a performance constraint[51, 52]. These optimization techniques were used to be applied in network replacement as a multi-objective problem [53]. The optimization technique allowed for the trade-off between cost of replacement and system performance. However, such techniques require large numbers of trial evaluations to obtain near-global optimal solutions. System availability as a performance measurement based on the Markov model was developed[50]. They modelled the states of deterioration of a pipeline and included the state of planned rehabilitation. Therefore, the decision about whether to replace or repair could be made to maximize the probability that the pipeline was operational at any time in its deterioration. Lansey, Basnet, and Woodburn [54] minimized rehabilitation cost based on a hydraulic performance constraint. They considered two-time steps such that works were scheduled for the current time and in 10 years. A similar approach restricted to a single time step was used by De Schaetzen, Randall-Smith, Savic, and Walters [55]. Engelhardt [53] extended this method by allowing the replacements to be scheduled over a 20 year period, which was split into four five-year time periods. The model enabled water pipelines replacements to be scheduled in any of these time intervals, with the expenditure in each period constrained by the available funds. This ability to schedule replacements over an extended period allowed for the various time-dependent parameters, for example, demand increases, to be included as part of the model.

A model was developed by Deb [56], which can extended planning horizon to identify the time to the next rehabilitation. A cycle time between replacements for each main in the network was proposed [56]. The model made the assumption that water pipelines currently in service were unlined metallic, whereas the water mains they would be replaced with would be either lined or non-metallic. The time to first replacement was thus a function of structural deterioration through corrosion and increase in hydraulic roughness. The duration between future replacements was purely a function of structural deterioration. Structural deterioration was considered as part of an economic analysis of future maintenance costs[57] in order to provide an optimum time of replacement. The deterioration in the hydraulic efficiency of the original water mains was modelled using the empirical hydraulic roughness model [58]. This model was in conjunction with the hydraulic solver EPANET to ensure that the pressures in the system remained above the minimum required, which attempted to extend the useful economic service life of the existing main by considering lining as opposed to replacement.

In a multi-objective approach, Halhal, Walters, Ouzar, and Savic [59] used the rehabilitation cost as a minimization objective and the maximization of the benefits of the rehabilitation schedule as a further objective. These benefits included the improvement in hydraulic performance of the rehabilitated system, its increased flexibility provided by including parallel mains, the economic savings of replacing mains that would experience bursts, and the water quality benefits associated with replacing old water mains. Except for savings associated with reduced numbers of bursts, the estimation of these benefits was very subjective. Farmani, Savic, and

Walters [60] reported a multi-objective approach. The first objective considered was the minimization of operating cost. A second objective was maximizing reliability, which was represented by a surrogate measure based on the number of customer interruptions. Raziyeh, Godfrey, and Dragan [61] investigated the application of multi-objective evolutionary algorithms to the identification of the payoff characteristic between total cost and reliability of a water distribution system. It reduced costs by reducing the diameter of some pipes, thus leaving the system with insufficient capacity to respond to pipe breaks or demands that exceed design values without violating required performance levels. Alvisi and Franchini [62] based on a multi-objective genetic algorithm proposed a near-optimal rehabilitation scheduling model, with reference to a fixed time horizon. The objectives were to minimize the overall costs of repairing and/or replacing pipes, and to maximize the hydraulic performances of the water network, whose constraints were represented by the maximum costs that were allowed yearly. A head-driven hydraulic simulator was linked to the optimizer to represent the different hydraulic and breakage scenarios, which became possible in consequence of the rehabilitation schedules generated by the genetic algorithm.

A multi-objective optimization algorithm NSGA-II, coupled with water distribution network simulation software EPANET, was proposed by Atiquzzaman, Shie-Yui, and Xinying [63] to provide Pareto front of the cost and nodal pressure deficit. However, this method was not proved in a large water network. Dandy and Engelhardt [6] used genetic algorithms to generate trade-off curves between cost and reliability for pipe replacement decisions. These can identify the trade-offs necessary for the current conditions and allowed the water authority to determine the required levels of future expenditure, given funding constraints, to meet a specified level of service over the entire planning horizon. A robust decision support tool for water system rehabilitation incorporated forecast pipe failures and a strategy to solve a multi-objective optimization problem trading investment and benefits was proposed by Giustolisi, Laucelli, and Savic Dragan[64]. They used a burst modelling approach, based on an evolutionary polynomial regression technique for predicting pipe bursts, which is used in a short-term planning. The result of this model can process which pipes were prioritized for rehabilitation based on the number of times, by considering costs and the priority rating of each main. Werey, Llerena, and Nafi [65] proposed a decision support model that ensures the scheduling of pipe renewal according to available financial resources based on forecasting pipe failures and evaluating future maintenance costs. They measured the undelivered water quantity and the number of unsupplied nodes when a considered pipe was unavailable during the peak demand period. Based on the results, by applying this model, the reliability of a water distribution network was enhanced. Zarghami, Abrishamchi, and Ardakanian [66] investigated integration of leakage detection on the water distribution network, water metering and on low volume water, and provided a model which derived optimum long-term plans for implementation of water resources. Di Pierro, Khu, Savic, and Berardi [67] proposed a model using multi-objective, hybrid algorithms, ParEGO and NSGA on the design problem of a real medium-size network in Southern Italy, and their results suggested that the use of both algorithms, in particular NSGA, could be successfully extended to the efficient design of large-scale water distribution networks. Nafi and Kleiner [68] focused on low-level scheduling of individual water mains, and proposed a model for the scheduling of individual water mains for replacement in a short-to-medium predefined planning period, subject to various budgetary constraints. A multi-objective genetic algorithm scheme was used as a tool to search a vast combinatorial solution space, comprising various combinations of pipe replacement schedules.

Researchers have provided various decision support tools to assist utility managers. Engelhardt et al. [69] and Rajani and Kleiner [70] provided comprehensive reviews on the approaches and methods that had been developed before 2001. Since then, some new tools have also been proposed. Sægrov [71] presented a decision support system CARE-W to allow selection and schedule of the rehabilitation jobs taking into account of deterioration. The system provides a hydraulic model for assessing the reliability of a pipeline network. Jarrett et al. [72] and Moglia et al. [11] developed PARMS-PLANNING and PARMS-PRIORITY based on risk calculation. These two models provide assistance in optimal replacement schedules for individual pipelines, including failure prediction, cost assessment, data exploration and scenario evaluation. Dandy and Engelhardt [6] developed a multi-objective genetic algorithm-based approach to finding out trade-off points between economic cost and reliability for scheduling replacement activities. Halfawy et al. [73] developed an integrated sewer renewal planning decision support system for estimating remaining service life and the probability of failure, and also for guiding inspection and renewal planning decisions. Sun et al [74] proposed a new approach for predicting the reliability of pipelines with multiple preventive maintenance cycles.

For practicality, when undertaking replacement planning, utility managers usually select two or three pipes, organised into one group for replacement, in order to meet some multiple objectives, i.e. minimization of costs, risks, and service interruptions, or maximizing reliability, and work efficiency. However, this practice fails to provide an optimal solution because of ambiguous criteria. Optimal group schedules need to take into consideration the multiple criteria such as costs, impact of service interruptions, pipe specifications, the type of technology employed and geographical information.

Some researchers have worked on scheduling grouping optimizations, although general group scheduling in replacement planning for water pipeline network has so far not received enough attention. Kleiner et al. [75] developed a renewal scheduling model for water main renewal planning, which takes account of life cycle costs and contiguity savings due to reduced mobilization costs by setting a contiguity discount. However, the model only considers two pre-determined situations where two pipelines share the same node and both are replaced in the same year. These pre-determined situations are not in accord with reality, because, in practice, pipelines, which are located in the same area, might be grouped together, even when they are not planned for replacement in the same year. Therefore, group scheduling for water pipe replacement decision optimisation is still an open research area, which may lead to bottom-line benefits for both utilities and customers to minimize total cost and limiting service interruption.

## 2.4 EVOLUTIONARY ALGORITHMS FOR MULTI-OBJECTIVE OPTIMIZATION

Multi-objective problems are problems with two or more objectives, and these objectives usually conflict. The main difference between multi-objective and single-objective optimization is that a multi-objective problem does not have one single optimal solution, but instead has a set of optimal solutions, where each represents a trade-off between objectives. [76]

One way to perform multi-objective optimization is using an evolutionary algorithm (EA). Evolutionary algorithms are optimizers inspired by natural evolution, and with the concept of survival of the fittest. In an EA, solutions to a given problem are considered individuals of a population, where the fitness of individuals is attributed by how well they solve the problem at hand. In the population, individuals may produce offspring, which makes parents and offspring compete for inclusion in the next generation. As only the most fit will survive, the full population improved iteratively in each passing generation.

Multi-objective evolutionary algorithm techniques can be traced back to 1985; Schaffer [77] presented an extension of the genetic algorithm method (vector evaluated genetic algorithm) in which the population in each generation is divided into sub-populations, with each sub-population being assigned a fitness on the basis of a different objective function. Then, through the development of multi-objective evolutionary algorithm, most of recent research can be identified as Pareto-based approaches.

Literature has shown a great number of contributions in this area. Multi-objective genetic algorithm (MOGA) begins with a ranking of the solutions based on the number of solutions that dominate it, and not all possible ranks will be represented in the population. The solutions are then sorted according to their raw fitness values (from rank 1 to largest rank found) and a linear function is used to assign an average fitness to each solution. Because of the computation methodology, the shared fitness of a high ranked solution can become more than that from a low ranked solution, which in effect can result in an inadequate selection pressure for better solutions. A non-dominated sorting genetic algorithm (NSGA)[78] was developed, in that it uses a non-dominated sorting procedure to calculate the raw fitness values as mentioned in the MOGA. Firstly, a rank 1 is assigned to all non-dominated solutions in the population. A dummy raw fitness value is assigned to each solution in this rank. The dummy fitness value for the rank 2 solutions is chosen as a number less than the minimum sharing fitness of rank 1 solutions. The process is repeated until every member of the population has been assigned a fitness values. Niched Pareto genetic algorithm (NPGA)[79] uses a modification of the binary tournament selection operator to include sharing information in a decision. No particular fitness value is assigned to a solution, and the quality of the solution is decided, entirely based on non-domination and a niche count. Distance-based Pareto genetic algorithm (DPGA) [80] is an elitist Multi-objective evolutionary algorithm (MOEA) which maintains a separate population, called the elite population *Et*, of non-dominated solutions, and assigns fitness to the general population, *Pt*, members based on distance comparison from the non-dominated ones. However, final fitness values in DPGA is dependent on the ordering of the solutions in the population, in which case it is not clear whether the diversity information is properly preserved or not. Strength Pareto Evolutionary Algorithm 2 (SPEA2)[81] as a modified form of Strength Pareto Evolutionary Algorithm (SPEA), which incorporates, in contrast to its predecessor, a fine-grained fitness assignment strategy, a density estimation technique, and an enhanced archive truncation method. Then SPEA2 was improved with a neighbourhood crossover, mating selection Applying archive to allow holding of diverse solutions in the objective space and variable space, which was named SPEA2+[82], which has a more effective crossover mechanism and an archive mechanism to maintain diversity of the solutions in the objective and variable spaces. A very popular elitist genetic algorithm for multi-objective optimization was the Non-dominated Sorting Genetic Algorithm (NSGA-II) [83]. It begins with a non-dominated ranking of the merged parent and child population. Parent population for the next generation, $P_{t+1}$, is created from the ranked solutions – low rank implies high preference. However, unlike most of the algorithms, NSGA-II do not have any parameters to tune, which has made it one of the most widely used MOEAs in engineering optimization problems. In recent year, a number of contributions were made to improve the NSGA-II for its efficiency. For example, a combined NSGA-II and SPEA2 selection with the Differential Evolution (DE) scheme for solution reproduction to create the Differential Evolution for Multi-objective Optimization (DEMO)[84]; A crowding distance method designed by minimum spanning tree to maintain the distribution of solutions for NSGA-II [85]; and a number of improvements on efficient constraint handling method for NSGA-II [86-88].

The basic problem of optimal distribution system maintenance has been usually considered as the minimization of an objective function representing the global system costs in order to solve the optimal sizing and/or locating problems for the distribution system. A number of research efforts for multi-objective optimization methods in distributed infrastructure networks can be found and the review follows.

Miranda [89] demonstrated a genetic algorithm approach to the optimal multistage planning of distribution networks. He described a mathematical and algorithmic model to solve the problems of the optimal sizing, timing and location of distribution substation and feeder expansion using genetic algorithms. However, he did not consider the multi-criteria methods in his research. In 1998, a new and efficient genetic algorithm was presented for the optimal design of large power distribution systems. It was similar to a mixed-integer nonlinear model, which takes into consideration of non-linear variable costs and linearized costs respectively [90]. Ramirez-Rosado and Bernal-Agustin[57] created a new evolutionary algorithm which is much faster than the classic one for finding out the best distribution network reliability and at the same time minimizing the system expansion costs. The algorithm determined the set of optimal non-dominated solutions, and allowed the planner to obtain the optimal locations and sizes of the reserve feeders that achieve the best system reliability with the lowest expansion costs, which are used in real life power systems. In contrast to "traditional optimization approaches which typically assess alternative planning solutions by finding the solution with the minimum total cost", Espie, Ault, Burt, and McDonald [91] proposed a methodology utilizing a number of discrete evaluation criteria within a multiple criteria decision making environment to examine and assess the trade-offs between alternative solutions. To demonstrate the proposed methodology, a worked example was performed on a test distribution network that forms part of an existing distribution network in one UK distribution company area.

In 2004, a combination of AHP with genetic algorithms to capture the capability of multi-criterion decision-making was proposed [92]. This algorithm allowed decision-makers to give weightings for criteria using a pairwise comparison approach, and provided more control on the determination of the optimization solutions. In 2006, Kandil and El-Rayes [93] developed a practical and automated system named the Multi-objective Automated Construction Resource Optimization System (MACROS), and it incorporated multi-objective optimization module, relational database module, middleware module and user interface module to simultaneously minimize project cost and duration while maximizing project quality. This system "generated optimal trade-offs among construction time, cost, and quality; visualized the generated optimal trade-offs among these three important objectives;

ranked the obtained optimal plans according to a set of planner-specified weights to facilitate the selection of an optimal plan that considers specific project needs; and provided seamless integration with commercially available project management software to benefit from its practical scheduling and control features". Carrano[94] presented a multi-objective approach for the design of electric distribution networks that considered the objectives of minimizing the overall costs and minimizing a system failure index. A MOGA, using problem-specific mutation and crossover operators and an efficient variable encoding scheme, was employed as the optimization machinery for finding the Pareto-optimal solutions. A genetic algorithm was used to solve the model, which evaluated the condition of elements, considered a budget constraint, and suggested the optimal maintenance schedule over a specified period of time. The extent of rehabilitation at a given time was considered as dependent on the present condition and amount of deterioration[95]. In 2009, Bernardon, Garcia, Ferreira, and Canha[96] created a new fuzzy multi-criteria decision making algorithm for network reconfiguration problem, which focused on power losses reduction. They chose the Bellman-Zadeh method[97, 98] for the fuzzy resolution methodology, promoting final solutions belonging to the Pareto objective space.

With infrastructure networks involving spatially distributed sites that have different work conditions, activities, and quantities, Hegazy[99] presented a formulation of a Distributed Scheduling Model (DSM), which was capable of generating schedules by manually changing the options for construction methods, number of crews, the site order, and the amount of interruption at various sites. Because the solution space of Distributed Scheduling Model would be extremely large, Hegazy [100] used Genetic Algorithms (GAs) to determine the optimum set of construction methods, for scheduling, resource planning, and cost optimization in large construction programs that involve multiple distributed sites. Using this distributed scheduling model, a practical model for scheduling and cost optimization of highway construction was presented[101]. Elhakeem [102] introduced a graphical approach (using Nomographs), in order to provide a transparent tool for quick manpower planning and sensitivity analysis. The Nomographs were utilized by practitioners to estimate the manpower needed to meet a predefined deadline, under anticipated network-level risks due to unfavourable site conditions. Subsequently, the scheduling model was applied not only to optimize the site order, construction methods and in-house crews, but also to suggest the location and frequency of outsourcing necessary to minimize the cost of delivery. Based on Hegazy's research, Elbehairy [103] presented a Multiple-element bridge management system (ME-BMS) that integrates both project-level and network-level decisions to enable the handling of large-size bridge networks with thousands of bridges. The life-cycle analysis also was formulated into two sequential optimizations for the project level and the network level, respectively.

## 2.5 CONCLUDING REMARKS

Through this literature review, the researcher finds that multi-objective maintenance decision optimization considering group scheduling is still an open area. In practice, replacement activities are usually scheduled in groups manually based on expert experience, and replacement decisions are made for groups of pipes case-by-case in order to improve work efficiency, and to reduce costs. This practice fails to provide an optimal solution, because the optimised replacement solutions cannot be determined only by user experiences. Moreover, much of the existing literature [6, 8, 11, 12] only focused on analysing scheduling optimisation for individual/single pipes, which provided replacement schedules for each single pipe to deliver an optimal replacement year. However, these efforts cannot satisfy the practical requirements for group scheduling optimisation in the following aspects:

(1) The requirement for integrating multiple criteria

Group scheduling needs to take into consideration multiple criteria, e.g. minimising geographical information, maximising equipment utilisation, minimising service interruption. Effective methods for modelling multiple group scheduling criteria are still not available in the literature.

(2) The requirement for cost and service interruption models to deal with cost and interruption reduction in terms of group scheduling pipes

Most of existing cost models and service interruption models for water pipe replacement were developed for individual water pipes, which cannot be directly applied for group scheduling, because the cost saving or interruption reduction based on group scheduling replacement cannot be calculated. Therefore, new costs model and service interruption models considering cost and interruption reduction needs to be developed.

(3) The requirement for optimisation algorithm to consider both replacement time and pipe allocation

    Group scheduling for water pipe replacement optimisation is complex in its large number of decision variables, which could be in both time and space domains. Through the literature review, it is seen that existing optimisation algorithms used for replacement optimisation cannot be applied directly to deliver optimal solutions. This is because they are unable to consider pipe allocation in the algorithm, so that they can only optimise replacement for single pipes rather than group scheduling of pipes. Therefore, a new optimisation algorithm to deal with pipe allocation and pipe replacement year is necessary for replacement group scheduling of water pipes.

Thus, based on the discussion above, effective methodologies for optimising of replacement scheduling for groups of pipes are still not available.

In order to deliver optimal replacement time for groups of pipes, reliability prediction analysis is crucial in this research. When analysing the reliability of water pipe, existing models often consider the entirety of the water pipes rather than the individual contributions of different components of the water pipes to the reliability of the water pipe system. A discrete hazard modelling method [104] was developed for general linear assets to deal with the effects caused by segmentation of pipes. However, this model has several limitations to deal with real water pipes.

(1) It is unable to handle the multiple failure characteristics and mixed failure distributions of water pipes

    Water pipes often present multiple failure characteristics and follow mixed failure distributions over their life spans. Failure records may contain distinctive distribution features in different groups, which can be identified with properly grouped pipes in terms of pipe length, diameter, material types, installation year, and soil types. One of fundamental limitations for applying the existing hazard model [13] is the requirement for the statistical grouping to partition assets data based on their specific features. Existing approaches [42, 43] in the literature, partition water pipes into groups on an ad hoc basis. Two limitations have been identified:

    a) Grouping relying on prior knowledge

b) Breakage rate following an exponential increase

However, prior knowledge of grouping criteria should be one of the results of grouping analysis, which is hardly available before any grouping analysis. The assumption of breakage rate following an exponential increase is, sometimes, not in accord with reality. Therefore, an effective approach for statistical grouping had not yet been developed in reliability analysis for water pipes.

(2) It is unable to deal with complex censorship pattern of lifetime data

In practice, maintenance histories are typically available for a relatively short and recent period, often less than a decade. The irregular, non-random distribution of pipe installations combined with the short observation period of failures often produce a complex censorship pattern, which is not amenable to treatment by existing hazard models in previous research. Existing hazard models may lead to underestimation of the true hazard for truncated lifetime data. The methods in hazard modelling for reliability prediction analysis to deal with truncated lifetime data have not been well developed.

(3) It is not clear about the application differences between two empirical hazard formulas.

Through literature review, two empirical hazard formulas can be derived from the theoretical hazard function[14-16]. One of the equations is commonly used to calculate empirical hazard. However, previous research did not investigate the difference of the two equations in terms of derivations and applications. This difference may result in deviation of calculating the empirical hazard.

# Chapter 3: Improved Hazard based Modelling Method

## 3.1 INTRODUCTION

Water pipes are typical linear assets, also called continuous assets. Linear assets are engineering structures that typically span long distances and can be divided into different segments. All segments perform the same function but may be subject to different loads and environmental conditions[41]. Linear assets play an important role in modern society, which include water pipes, sewer pipes, roads, railways, oil and gas pipelines and electricity distribution networks.

Reliability analysis and failure prediction for linear assets have attracted a great deal of attention from engineering asset management. However, reliability prediction of linear assets is still a great challenge in practice. A fundamental issue is the segmentation of linear assets and data grouping for reliability analysis. A single linear asset may be subject to various working environments, having different failure rates in different areas, and thus needs to be divided into distinct segments for reliability analysis[41]. Therefore, every linear asset can be treated as a chain structure, where the success of the whole asset depends on the success of all the segments of this asset. In other word, if one segment fails, the relevant asset will be treated as failed. However, the failure of one segment of the asset cannot affect the reliability of other segments, due to its long length. A sketch to illustrate the segmentation of water pipe is shown in Figure 3-1.

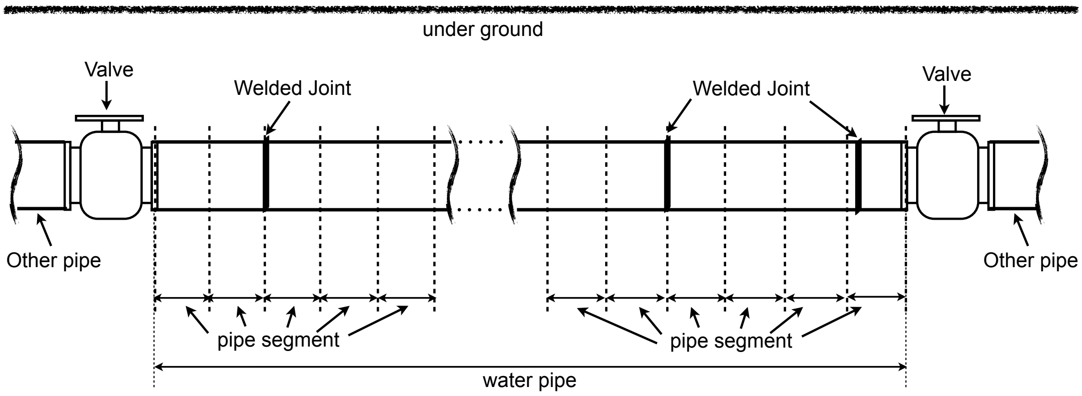



Figure 3-1 Sketch of water pipe segmentation

Take water pipe as an example. A water pipe can be considered as a combination of a number of small length segments. A segment has identical diameter, material, with identical soil condition. One segment's failure causes the whole pipe to lose its functionality. From the data analysis point of view, the recorded failure history is for water pipes rather than pipe segments. This type of record presents a gap between the data required for reliability analysis and real failure history records.

Sun[13] proposed a discrete hazard based modelling method for linear assets. He assumed the lifetimes of assets followed a piece-wise distribution. His method can effectively model the hazard of linear assets based on segmentation. However, a number of improvements are required to achieve accurate prediction results: (1) linear assets often present multiple failure characteristics and follow mixed failure distributions over their life spans. It is compulsory to partition water pipes into characteristically more homogeneous groups; (2) truncated lifetime data may cause underestimation of the true hazard.

Therefore, an improved hazard modelling method for linear assets is developed for analysing the reliability of water pipe system. This chapter starts with an introduction of the piece-wise hazard model developed by Sun in Section 3.2, followed by a statistical grouping algorithm in Section3.3, which partitions all the water pipes into characteristically more homogeneous groups. For each homogeneous group, a theoretically sound and accurate empirical hazard function for linear assets is necessary for analysing lifetime distribution of the continuous-time failure data, two commonly used empirical hazard function are investigated and compared in terms of their derivations and applications in Section3.4. In Section 3.5, an empirical hazard function to deal with truncated lifetime data, and a hazard distribution fitting method for an extreme situation are developed, where the extreme situation indicates large proportion of length of pipes were repaired in the observation period. A Monte Carlo simulation framework based on a real water utility is developed and a test-bed sample dataset are generated based on the main features of the real data of a water utility to test and validate the proposed empirical hazard function and the hazard distribution fitting method in Section 3.5. Finally, Section 3.6 introduces the procedure of the improved hazard modelling method for linear assets.

In this chapter, only water pipe is considered for the purpose of model validation through a case study. The contribution of the proposed improved hazard modelling method can be applied to all linear assets.

## 3.2 THE DISCRETE HAZARD BASED MODELLING METHOD FOR LINEAR ASSETS

### 3.2.1 Piece-wise hazard model for linear asset

The bathtub shape curve is a common failure rate pattern for many engineering assets/components over their lifetimes. The bathtub hazard curve can be divided into three parts as shown in Figure 3-2 [105].

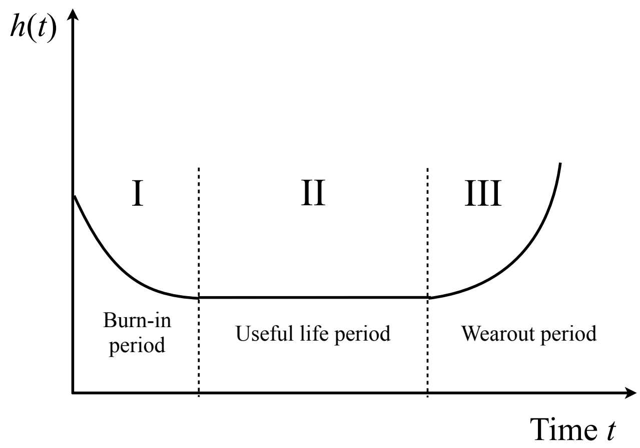



Figure 3-2 Bathtub hazard rate curve

Various models have been proposed to describe the mixed distributions[33, 106, 107]. Sun[13] proposed a piece-wise hazard model for linear assets. In his model, he assumed that Phase I is either very short or the burn-in factors are insignificant for most linear assets. Therefore, Phase I is not obvious, which leads to the hazard pattern shown in Figure 3-3.

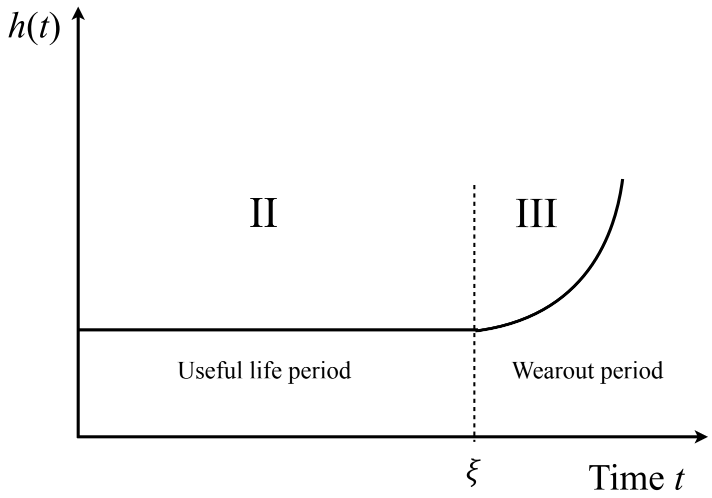



Figure 3-3 Typical two-phase failure pattern for linear assets

In Sun's model, the hazard in Phase II (useful life period) follows a constant failure rate due to pure random factors, such as undetectable defects, higher random stress than expected, human errors. In Phase III (wear-out period), the hazard rate increases, caused by the joint contribution of the assets ageing and random factors. An equation to describe the piece-wise hazard pattern is given by:

$$h(t) = \begin{cases} \lambda & , \ 0 \leq t < \xi \\ \lambda + \frac{\beta(t-\xi)^{\beta-1}}{\alpha^{\beta}} & , \ t \geq \xi, \alpha > 0, \beta > 1 \end{cases} \tag{3-1}$$

where $\lambda$ is a constant failure rate, $\xi$ indicates the start time of Phase III, $\alpha$ and $\beta$ are the scale and shape parameters of the Weibull distribution in Phase III, respectively. Phase II with a constant failure rate is actually an exponential distribution, where the exponential distribution is suitable to describe the failure time patterns due to random causes, such as sudden excessive loading or a natural disaster. Phase III described the joint contribution of the assets ageing and random failure, which follows a joint distribution of exponential and Weibull, where Weibull distribution has great flexibility in construction of different shapes of hazard curves, in particular, the bathtub shape hazard curve.

The piece-wise hazard model in the wear-out period ($t \geq \xi$) proposed by Sun[13], is actually a simplified bi-Weibull Model [14, 108], where the hazard function is given by:

$$h(t) = \frac{\beta_1 \cdot t^{\beta_1 - 1}}{{\alpha_1}^{\beta_1}} + \frac{\beta_2 \cdot t^{\beta_2 - 1}}{{\alpha_2}^{\beta_2}}, \tag{3-2}$$

where $\alpha_1$ and $\alpha_2$ are the scale parameters for two independent Weibull distributions, and, $\beta_1$ and $\beta_2$ are the shape parameters for the two independent Weibull distributions. The density function of the bi-Weibull model corresponds to the smaller one of the two independent Weibull distributions. The piece-wise hazard function can be derived from bi-Weibull distribution, where one of the shape parameters $\beta_1$ or $\beta_2$ equals "1". Therefore, the piece-wise model in the wear-out period ($t \geq \xi$) follows the joint distribution of exponential and Weibull distributions Based on the bi-Weibull distribution, the probability density function (pdf), cumulative distribution function (cdf) and the reliability function of the piecewise model are given by:

pdf

$$f(t) = \begin{cases} \lambda \cdot e^{-\lambda t} & , \ 0 < t < \xi \\ \frac{\beta (t-\xi)^{\beta-1}}{\alpha^{\beta}} \cdot e^{-\left(\frac{t-\xi}{\alpha}\right)^{\beta}} & , \ t \geq \xi, \alpha > 0, \beta > 1 \end{cases}, \tag{3-3}$$

cdf

$$F(t) = \begin{cases} 1 - e^{-\lambda t} & , \ 0 < t < \xi \\ 1 - e^{-\lambda t} \cdot e^{-\left(\frac{t-\xi}{\alpha}\right)^{\beta}} & , \ t \geq \xi, \alpha > 0, \beta > 1 \end{cases}, \tag{3-4}$$

and reliability function

$$R(t) = \begin{cases} e^{-\lambda t} & , \ 0 < t < \xi \\ e^{-\lambda t} \cdot e^{-\left(\frac{t-\xi}{\alpha}\right)^{\beta}} & , \ t \geq \xi, \alpha > 0, \beta > 1 \end{cases}. \tag{3-5}$$

Figure 3-4 shows the nature of the functions associated with the piece-wise model for $\xi = 30$, $\lambda = 0.01$, $\beta = 1.1$, and $\alpha = 50$. The upper left graph indicates failure density function; the upper right is failure distribution function; the lower left showed reliability function; and the lower left illustrated hazard function.

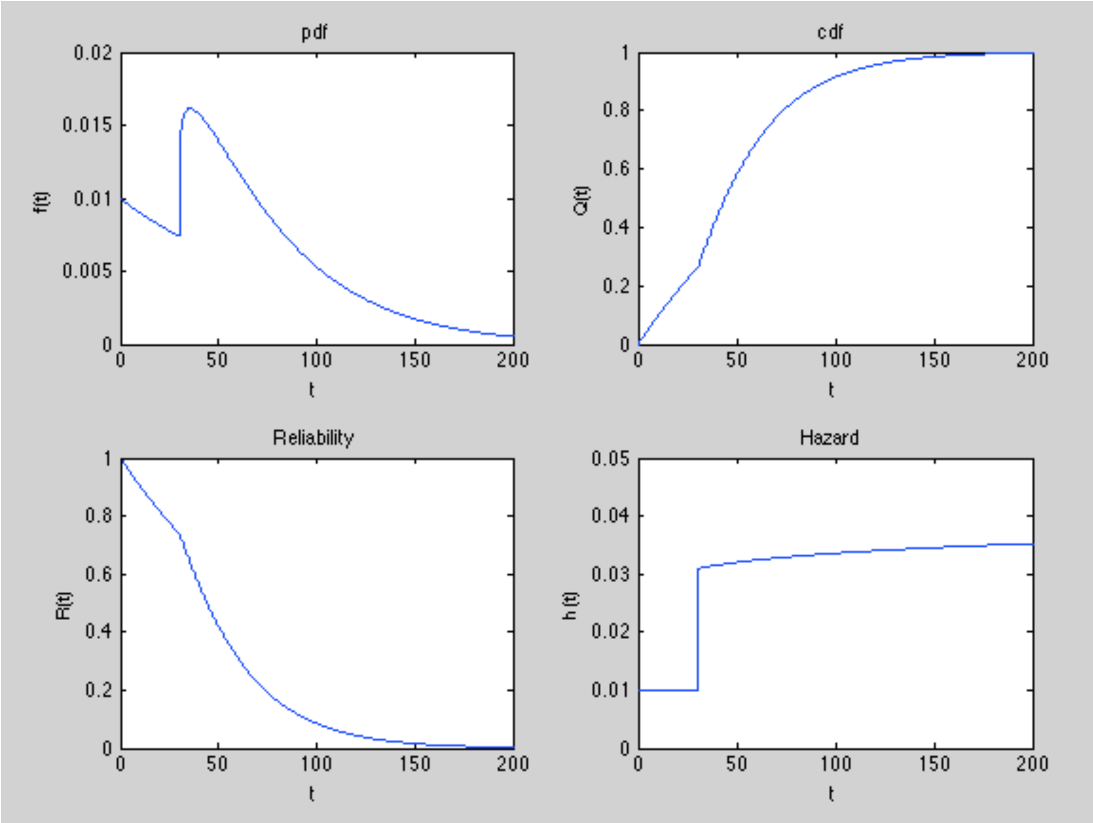



Figure 3-4 PDF, CDF, reliability and hazard function of the piecewise hazard model

Moreover, a discrete hazard equation was used by Sun [13] as:

$$\hat{h}_i = \frac{N(t_i) - N(t_i + \Delta t)}{\Delta t \cdot N(t_i)}, i = 1,2, \ldots,$$

where $N(t_i + \Delta t)$ is the number of functional units at time $t_i + \Delta t$, $\Delta t$ is the time interval.

This equation indicates that for a population of asset units, their hazard at time *t* can be estimated by dividing the number of failed units between times t and $t + \Delta t$ by the product of time interval $\Delta t$ and the number of functional units at time *t*. Sun [13] made conclusions that this approach is particularly suitable for linear assets as they usually have a number of the same or similar segments.

Furthermore, a linear regression and a non-linear regression approach to estimate the parameters of the piece-wise hazard model were also applied by Sun[13]. He pointed out that if the data are sufficient, the wear-out point, $\xi$, will be identified directly from a hazard bar chart. Otherwise, expert knowledge is needed to estimate it. The dataset is divided into two subsets. One contains the hazard values before $\xi$, and the constant failure rate in Phase II can be calculated by taking the average value of the discrete hazard rates. The other subset contains the hazard values after $\xi$. The other parameters of the discrete hazard model can be estimated using non-linear regression.

### 3.2.2 Assumptions of the piece-wise hazard model

The failure of water pipe can lead to severe disasters such as flooding the road, damaging the surrounding infrastructure and decreasing the pressure of water supply so as to interrupt service to customers. The failure of one pipe segment may affect the condition of other pipe segments adjunct to the failed segment. For example, their conditions may be degraded by the floodwater. In practice, it is difficult to analyse the effects because of lack of relevant information and records. To simplify the analysis, three important assumptions were made by Sun[13] to specify the hazard calculation for linear assets:

1. Assets are independent to each other, so that one asset's failure cannot affect the condition of other assets;
2. For every linear asset, segments are independent to other segments, so that one segment's failure cannot affect the reliability of other segments;
3. For one asset, no more than one segment fails at the same time;

The condition of the repaired segment is "as good as new", meanwhile, the condition of the whole asset remains "as bad as old", for the reason that repaired segments, normally only take small proportions of the whole assets.

## 3.3 STATISTICAL GROUPING ALGORITHM FOR HAZARD MODELLING

As previously mentioned, there is a practical challenge for hazard modelling of linear assets failure/maintenance data, because linear assets often present multiple failure characteristics and follow mixed failure distributions over their life spans. To automatically partition pipes into more homogeneous groups, existing approaches in the literature have the following limitations: (1) grouping criteria need to be determined firstly based on prior knowledge, then the pre-decided groups were tested by some methods. In general, the prior knowledge of grouping criteria is the one that needs to be investigated. (2) They assumed the breakage rate following an exponential increase, which in some cases is not in accord with the facts.

To deal with these limitations, and to improve the current piece-wise hazard model, a statistical grouping algorithm is developed based on a regression tree. The reasons for applying regression tree in this research are as follows: (1) it is a non-parametric, so that this method does not require specification of any functional form; (2) it does not require variables to be selected in advance, where the regression tree algorithm will identify the most significant variables and eliminate non-significant ones; (3) its results are invariant to monotone transformations of its explanatory variables, where changing one or several variables to its logarithm or square root will not change the structure of the tree; (4) it can easily handle outliers, and it will isolate the outliers in a separate node, which is very significant, because pipe data very often have outliers due to different materials in different installation years; (5) it has no assumptions, so that it can very easily handle the complexity of the data grouping for water pipes.

This algorithm uses recursive partitioning to assess the effect of specific variables on pipe failures, thereby ultimately generating groups of pipes with similar distribution features, where homogeneity of the resulting subgroups of observations can be achieved.

### 3.3.1 Statistical grouping algorithm based on regression tree

***Techniques of Regression Tree***

Regression trees approach deals with numerical response variables ***Y*** along with a set of explanatory variables $\boldsymbol{X}$, where $\boldsymbol{X} = (\mathbf{X_1}, \mathbf{X_2}, \ldots, \mathbf{X_u})$, and $u$ indicates the number of explanatory variables. Regression trees represent a multi-stage decision process, where a binary decision is made at each stage[109]. The tree includes nodes and branches. Nodes are designated as internal or terminal nodes, where internal nodes can be split into two children, while terminal nodes do not have any children, and they are associated with the average value of the response variable. The regression tree can be used to examine all independent variables $\boldsymbol{X}$ for all possible splits and chooses the split that yields the smallest within-group variance in the two groups, such that the two groups are homogeneous with respect to the response variable ***Y***.

Figure 3-5 shows the structure of regression trees [110], where *t* with circles indicate intermediate nodes and *t* with squares show the terminal nodes with predicted values of response variable *y*(*t*).

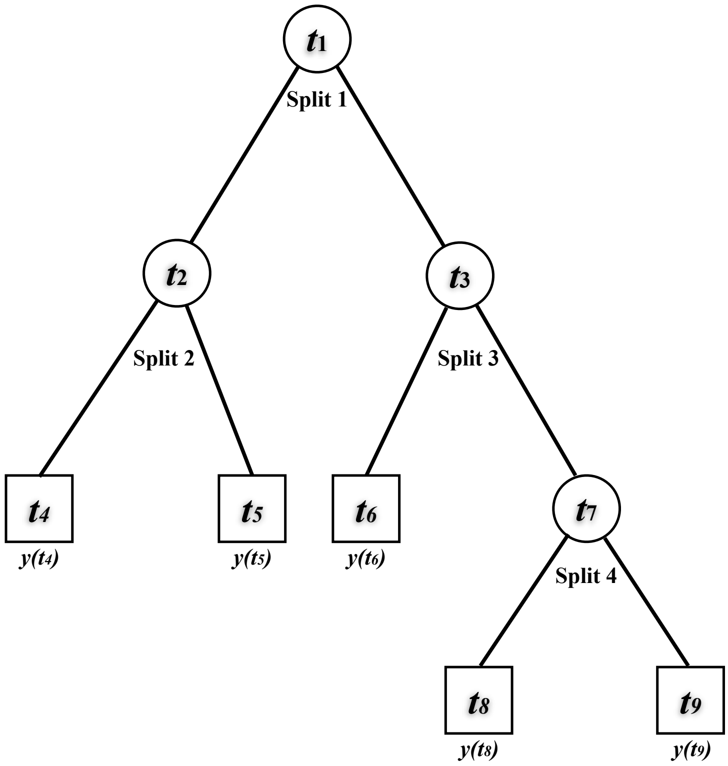



Figure 3-5 Regression tree structure

***Variables of the statistical grouping algorithm for water pipes***

Grouping for water pipes is used to investigate the homogeneous groups for pipe failures based on the explanatory variables and response variable. The variables are discussed and determined as below:

*Explanatory variables*

Pipe material is one of the most important factors for pipe failure. The properties of pipe material include impact resistance and corrosion resistance. Impact resistance is a material's ability to absorb an impact without damage[111]. Pipe failure might occur if a rock fell on the pipe in a trench or if the pipe was dropped. The rigidity and flexibility of different materials indicate how the pipe will react to impacts. Pipes made of rigid material sustain applied loads by means of resistance against longitudinal and circumferential bending. Rigid material includes all concrete (MSCL, CICL and DICL), cement (AC and FRC) and cast iron pipe. Pipes made of flexible material can deflect more than 2% of their diameter without any sign of structural failure. Flexible material includes all metal for example steel and copper except cast iron, and all plastic material (PVC, UPVC, HDPE and MDPE). Corrosion resistance is another material's ability to resistant water pipe failure. Some materials are more intrinsically resistant to corrosion than others. Metal pipe corrosion is a continuous process of ion release from the pipe into the water, while plastic and concrete pipes tend to be resistant to corrosion. Due to the differences among the properties of different materials, pipe material is selected as one of the important explanatory variables in this grouping analysis.

Pipe diameter is a variable, which can affect the failure of water pipes. Commonly, pipes with small diameter have high frequency of failures, for the reason that small diameter pipes have thinner thickness walls, reduced pipe strength, and less reliable joints. On the contrary, pipes in large diameter have greater thickness walls, with more resilient structure for durability, resulting in longer lifetime compared with small diameter pipes.

The length of water pipes differs from pipe to pipe in a water distribution network. One pipe is considered to be composed of a number of segments, and each segment is greater and equal to one metre. Different joint methods are used to join pipe segments in long length. Therefore, longer pipes are combined with more joints, which have more potential to failure.

*Response variable*

The definition of hazard is the instantaneous rate of failure happening in an asset, where the asset has not failed yet. One of the objectives of grouping analysis is to distinguish hazard curves from each other between groups. Therefore the response variable of grouping must consist of two features: (1) it can reflect the feature of hazard; and (2) it can be calculated for each single pipe. Therefore, the number of failures per unit length for each single pipe is identified as the response variable in the statistical grouping algorithm.

Based on the description above, in this research, the response variable $\boldsymbol{Y}$ represents the number of failures per unit length, and the independent variables $\boldsymbol{X}$ include $\boldsymbol{X_1}$ (pipe length), $\boldsymbol{X_2}$ (pipe material), and $\boldsymbol{X_3}$ (pipe diameter).

***Procedure of the statistical grouping algorithm***

A four-step procedure illustrated in Figure 3-6 was applied to deal with the grouping for calculating empirical hazard.

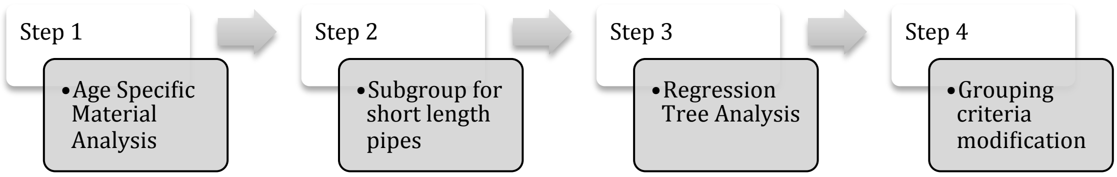



Figure 3-6 Procedure of the proposed statistical grouping algorithm

*Step 1: Age specific material analysis*

Firstly, the number of failures per unit length over average age for each material type is calculated and compared. Because pipe material plays an important role in water pipe failures and there is a strong correlation between pipe material and installation year, this correlation can dominate the grouping analysis using a regression tree. Therefore, in Step 1, extreme values are selected as criteria to partition water pipes into subgroups.

*Step 2: Subgroup for short length pipes*

Manually form a subgroup with all pipes, which are equal to and shorter than one metre in length, separated from all pipe subgroups identified from Step 2. (Based on the fact that failures/repairs occurring on pipes less than one metre in length are most likely to be fundamentally different from those longer pipes, e.g. they include joints and elbow sections. It is also reasonable to make this modification due to the assumption condition 2, showed in the next section.)

*Step 3: Regression Tree analysis*

Regression trees method is used to partition subgroups of pipes in Step 1 and Step 2 considering the explanatory variables of length, diameter, and material type. Regression trees method identifies mutually exclusive and exhaustive subgroups of a population, whose members share common characteristics that influence the response variable of interest.

*Step 4: Criteria modification*

The grouping criteria generated from Step 3 for length and diameter are in decimal number, which sometimes is not reasonable. For example, there is no practical meaning for a diameter equalling to 125.4mm. Therefore, a modification is needed to round the decimal numbers.

***Assumptions of the statistical grouping algorithm***

(1) All work recorded in repair history is treated as failure records (e.g. ignoring the possibility that a recorded work could actually be an inspection only.).

(2) One metre is used as the unit-length of a pipe in calculating the empirical hazard (i.e. failure rate). The assumption is made such that no more than one repair will occur at the same time to the same unit-length of a pipe. Even the repaired unit-length may be “as good as new” (in the case of replacement that has occurred), the whole pipe’s characteristic will still be considered “as bad as old” for the repaired length, because this is normally much less than the total length.

(3) The empirical hazard distribution is defined as the age-specific failure rates. For the water pipe case, the failure rate (or empirical hazard) is defined as

**Number of failures** per **metre** per **year**,

which is calculated as

**Repaired length of age-specific year** divided by **total length in operation at the beginning of the age-specific year**.

The number of failures/repairs per unit length (with respect to each individual pipe) is used as the statistical grouping criterion, which complies with the above definition of age-specific failure rate.

### 3.3.2 A case study to test the proposed statistical grouping algorithm

The case study for testing the proposed statistical grouping algorithm is based on a selected data set from a real water utility. Four types of materials (AC, DICL, CICL, MS) for water pipes were selected.

### *Data used for statistical grouping algorithm*

The data for grouping were given in two files:

1. Work order sheet: work order sheet recorded the failure/repair date of each repair activity, and there were 3,400 sets of failure/repair records from 2002 to 2012;
2. Asset sheet: asset sheet recorded the general information of each pipe with pipe length in metres, pipe diameter in millimetres, pipe materials, and pipe installed date. The asset sheet consists of 40,653 sets of valid records.

(The raw data cannot be presented due to the need for confidentiality.)

### *Application Results*

#### *Step 1 outputs*

The unit length in this case study is equal to 100m. Pipe material type is a major factor or parameter in terms of grouping. From Step 1, the number of failures per 100m over average age for each material type was calculated, and was shown in Figure 3-7. It can be observed from Figure 3-7 that DICL had the shortest average life, and CICL had the longest average life. MS was considered as an outlier, because it showed an extremely high value of failures/100m. This was caused by a fact that one failure record and only 132.81 metres of pipe exist for this MS material in the entire network. Thus MS will be excluded in the regression tree analysis in Step 2.

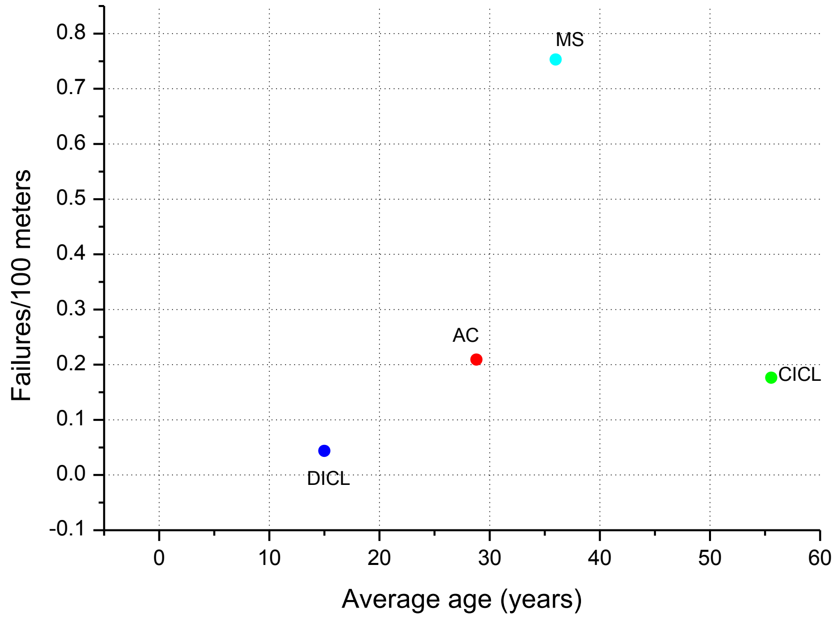



Figure 3-7 Relationship between failures/100m and average age for each material type

*Outputs from Step 2*

From Step 2, all pipes except MS pipes manually form a subgroup, where the pipe length is equal to and shorter than one metre. On the other hand, all pipes excluding MS pipes were partitioned using the regression tree. The results are shown in Figure 3-8, indicating that all pipes were partitioned based on length shorter than and equal to 0.89 metre. The result is very similar to the assumption in Step 2.

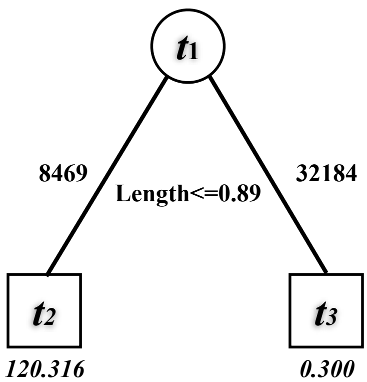



Figure 3-8 Regression tree for grouping of all pipes except MS pipes

*Outputs from Step 3 and Step 4*

Figure 3-9 shows the regression tree of grouping for pipe length greater than one metre except MS pipes. It has three splits with four terminal nodes. The first split ($t_1$) (Material = AC) separates off 18,884 tracts with the high average *NORP100M* of 0.624 from 13,195 tracts with a low average of 0.163. Then the left branch is split on Diameter <= 125mm ($t_2$), with 10,835 tracts having high average *NORP100M* of 0.811 ($t_3$), and with 8,049 tracts having lower average of 0.370 ($t_5$). The other branches can be similarly followed down and interpreted. The regression tree showed in Figure 3-9 has eight terminal nodes, $t_4$, $t_5$, $t_6$, and $t_7$, which indicates that based on the regression tree for pipe length greater than one metre, four groups were partitioned. In Step 4, the diameter value of 336.6mm was rounded as 337mm.

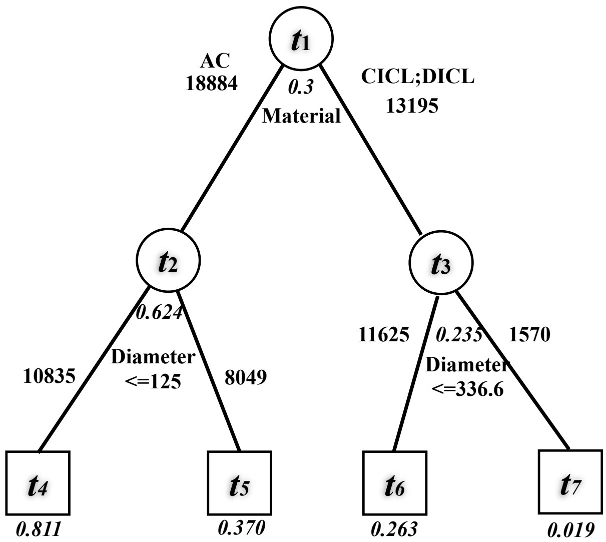



Figure 3-9 Regression tree of grouping for pipe length greater than one metre except MS pipes

Table 3-1 shows the final results of statistical grouping from Step 1 to Step 4. All pipes were partitioned into six groups, with the listed grouping criteria, number of pipes, number of failure records, and percentage of total number of failures.

Table 3-1 Split groups based on the proposed statistical grouping algorithm

| Group | Criteria (Material, length, diameter) | Number of pipes | Number of failure records | Total number % |
|---|---|---|---|---|
| 1 | Length>1m, Diameter<=125mm, AC | 10,835 | 2,224 | 65.41 |
| 2 | Length>1m, Diameter>125mm, AC | 8,049 | 810 | 23.82 |
| 3 | Length>1, Diameter <=337mm, CICL, DICL | 11,625 | 286 | 8.41 |
| 4 | Length>1m, | 1,570 | 29 | 0.85 |

| | | | | |
|---|---|---|---|---|
| | Diameter >337mm, CICL, DICL | | | |
| 5 | Length<=1, all materials without MS | 8,562 | 50 | 1.47 |
| 6 | MS | 12 | 1 | 0.03 |
| | Whole group | 40,653 | 3,400 | 100 |

This case study only selected data with five materials; therefore, the failure records for Group 4, Group 5 and Group 6 are not sufficient for hazard analysis. The calculated empirical hazards in most of the ages are equal to “0”, which makes it difficult to see the trends of the hazards in these groups through the calculated empirical hazard values. Therefore, smoothed line patterns were calculated to show the trends of hazard in each group, based on the Savitzky–Golay[112] smoothing filter. The Savitzky–Golay[112] smoothing filter performs a local polynomial regression on a series of values to determine the smoothed value for each point. In this case study, a window size of 7 points is selected to smooth the empirical hazard of Group 4 and Group 5. For Group 1 to Group 3, the failure records are sufficient; therefore, empirical hazards were calculated for Group 1 to Group 3. Group 6 only has one failure record, hence it is unable to show hazard trend, and therefore, it is excluded in hazard analysis.

Figure 3-10 and Figure 3-11 show the empirical hazard for Group 1 to Group 3 as well as the whole group, and smoothed line patterns for Group 4 and Group 5. It can be seen that the empirical hazard curves and smoothed hazard curves between groups are clearly distinctive from each other. The hazard curve of Group 5 in Figure 3-10 stands out due to its extraordinary short total length (hence resulting in some very high empirical hazard values).

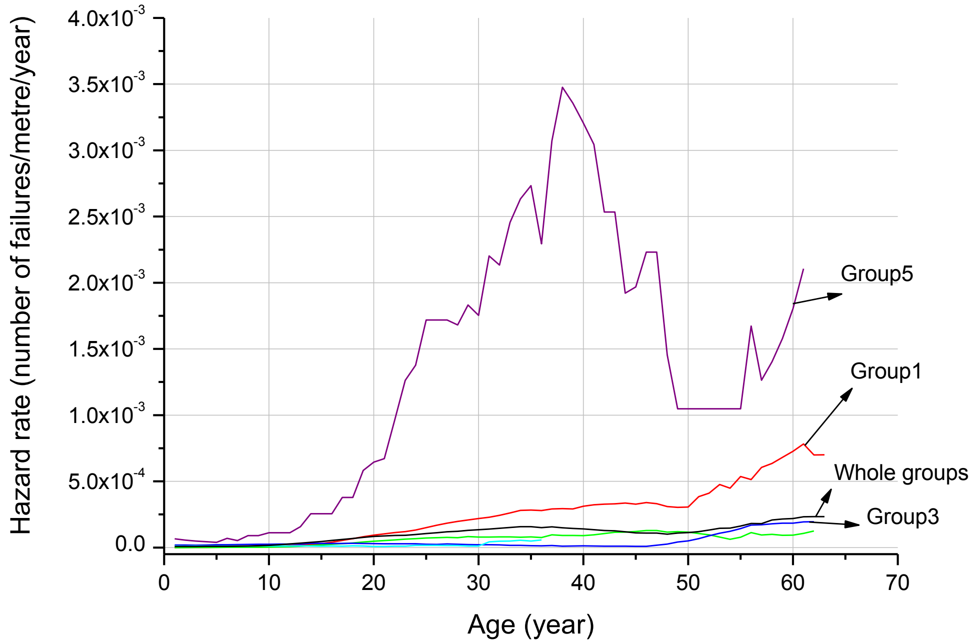



Figure 3-10 Empirical hazard and smoothed line patterns (Excluding Group 6)

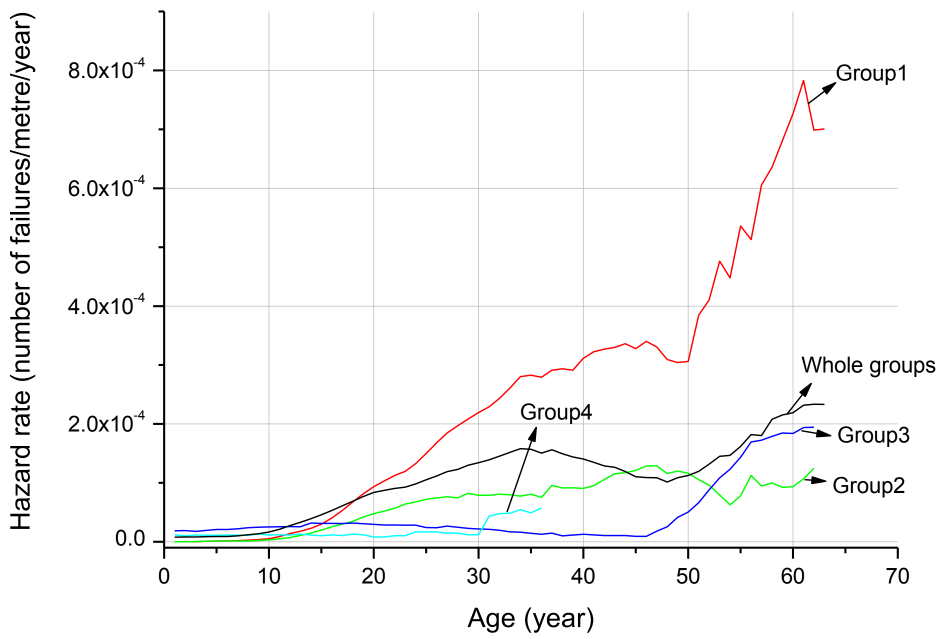



Figure 3-11 Empirical hazard and smoothed line patterns (excluding Group 5 and Group 6)

From Figure 3-11, Group 1 shows higher values and more dramatically increasing trend than other groups, which comply with the fact that AC pipes with small diameters have higher a probability of failure than others. The hazard curve of Group 3 rises more dramatically than the curve of Group 4, which indicates that for CICL and DICL pipes, larger diameter pipes have lower increasing trends than small diameter pipes. By applying the statistical grouping algorithm, the hazard curves between groups can be clearly separated from Group 1 to Group 5.

Given the above grouping results, it is recommended that the statistical grouping algorithm applied in this research can be adopted as a general grouping methodology in linear asset failure time data analysis.

## 3.4 THEORETIC FORMULAS OF EMPIRICAL HAZARDS, AND EVALUATION

Once all pipes in the network were partitioned into homogeneous groups with similar characteristics based on the statistical grouping algorithm introduced in the previous section, a theoretically sound and accurate empirical hazard function can be used directly for analysis of life time distribution of the continuous-time failure data. This section starts from clarifying the relationship between the concepts of hazard function and failure rate. Then, two often-used continuous-time data empirical hazard function formulas are derived directly from discrediting their theoretic definitions of the hazard function. The properties of these two different formulas are investigated and their estimation performances against the true hazard function values are compared using simulation samples [113].

### 3.4.1 Introduction of empirical hazard function

Hazard function plays an essential role in the application of probability theory in engineering reliability study. For example, the Mean Time To Failure (MTTF) is calculated as the inverse of hazard rate if the asset system lifetime distribution is assumed to follow an exponential distribution. In the data analysis stage, the term failure rate is more often used when trying to work out the MTTF. Hazard or hazard rate $h_i \equiv h(t_i)$ is the instantaneous failure rate at a time instant $t_i, i = 1,2,\cdots$. However, failure rate in data analysis is more often a short term for Average Failure Rate (AFR) over a time period $t_2 - t_1$ (assuming $0 \le t_1 < t_2$). AFR can be calculated using formula [33]

$$\text{AFR} = \frac{\int_{t_1}^{t_2} h(u)du}{t_2 - t_1}. \quad (3\text{-}6)$$

Equation (3-6) is the average hazard function formula which is considered as the most typical estimation of the true hazard function values [114]. Therefore, an empirical hazard function formula is necessary, so that the hazard function $h(t)$ can be estimated based on observed sample data.

Sample failure time data can be treated as discrete data, i.e. the observed sample failure times are considered as the events that occur at pre-assigned times $0 \leq t_1 < t_2 < \cdots$, and that under a parametric model of interest the hazard function at $t_i$ is $h_i = h(t_i|\theta)$. A set of intervals $I_i = [t_i, t_{i+1})$ covering $[0, \infty)$ for an engineering asset system is considered with $N$ functional components at $t_1 = 0$. Let $d_i = N(t_i) - N(t_{i+1})$, where $N(t_i)$ and $N(t_{i+1})$ are the numbers of components, which are functional at time $t_i$ and time $t_{i+1}$, respectively. Then the quantity $d_i$ is the number of failures in interval $I_i$, and $r_i \equiv N(t_i)$ is the number of components at risk (i.e. having the potential to fail) at $t_i$. It can be shown that the maximum likelihood estimator (MLE) is

$$\hat{h}_i = \frac{d_i}{r_i}, \quad (3\text{-}7)$$

from which the well-known Kaplan-Meier estimator for the reliability function

$$\hat{R}(y) = \prod_{i:t_i<y}(1 - \hat{h}_i) = \prod_{i:t_i<y}\left(1 - \frac{d_i}{r_i}\right),$$

is derived. Equation (3-7) is valid under independent right censoring [14, 115]. Note that the Kaplan-Meier estimator is also valid for randomly censored data. For the randomly censored data, the formula for the calculation of $d_i$ should be modified as

$$d_i = N(t_i) - N(t_{i+1}) - N_{c(i)}, \quad (3\text{-}8)$$

where $N_{c(i)}$ is the number of components being censored in interval $I_i$.

In data analysis practice, the sample failure time data is treated as continuous-time data as shown in Equation (3-6). Two often-used empirical hazard function formulas for treating the continuous-time data are:

$$\hat{h}_i = \frac{N(t_i)-N(t_i+\Delta t)}{\Delta t \cdot N(t_i)} = \frac{1}{\Delta t}\frac{d_i}{r_i} \equiv \widehat{h1}_i, \tag{3-9}$$

and

$$\hat{h}_i = -\frac{1}{\Delta t}\log\left[1-\frac{N(t_i)-N(t_i+\Delta t)}{N(t_i)}\right] = -\frac{1}{\Delta t}\log\left(1-\frac{d_i}{r_i}\right) \equiv \widehat{h2}_i, \tag{3-10}$$

where 'log' represents the natural logarithm operation. The notation $\Delta t \equiv t_{i+1} - t_i$ is used to emphasize that failures can happen at any time instants, not necessarily at $t_i, i = 1,2,\cdots$ under the continuous-time data setting. The same cares need to be taken in applying Equations (3-9) and (3-10), when calculating the empirical hazards for the censored data. Equation (3-8) needs to be applied in calculating $d_i$.

### 3.4.2 Empirical hazard function derivation and discussion

The following definition and relationship equations for the hazard function can be found in any standard textbook on failure time data analysis. It is assumed that the time to failure *T* is a random variable, which can take any value in the interval $[0, \infty)$. The hazard function of *T* is defined as

$$h(t) = \frac{f(t)}{1-F(t)} = lim_{\Delta t \to 0}\frac{F(t+\Delta t)-F(t)}{\Delta t \cdot (1-F(t))}, \tag{3-11}$$

where $f(t)$ and $F(t)$ are the pdf and cdf of *T*, respectively.

Since $f(t) = \mathrm{d}F(t)/\mathrm{d}t$, after further algebra, another form of the definition for the hazard function is given as

$$h(t) = -\frac{\mathrm{d}[\log(1-F(t))]}{\mathrm{d}t} = lim_{\Delta t \to 0} - \frac{\log(1-F(t+\Delta t))-\log(1-F(t))}{\Delta t}. \tag{3-12}$$

By discretising Equations (3-11) and (3-12) respectively, the hazard function is given as:

$$\hat{h}(t) = \frac{F(t+\Delta t)-F(t)}{\Delta t \cdot (1-F(t))}, \tag{3-13}$$

and

$$\hat{h}(t) = -\frac{\log(1-F(t+\Delta t))-\log(1-F(t))}{\Delta t} = -\frac{1}{\Delta t}\log\left[\frac{1-F(t+\Delta t)}{1-F(t)}\right]. \tag{3-14}$$

Given the early defined notations *N*, $N(t_i)$, $\Delta t \equiv t_{i+1} - t_i$ and $h_i \equiv h(t_i)$, the relative frequency as the estimator for $F(t_i)$ is given as:

$$F(t_i) \approx \frac{N-N(t_i)}{N} = 1 - \frac{N(t_i)}{N}. \tag{3-15}$$

By applying Equation (3-15) to Equations (3-13) and (3-14) accordingly, after some algebras, Equations (3-9) and (3-10) are derived, where ‘log’ represents the natural logarithm operation.

Up to this point, it is clear that both formulas (3-9) and (3-10) converge to the true values of $h_i$ as $\Delta t$ approaches zero. Note that this asymptotic property of convergence still hold after the introduction of Equation (3-15) in the derivation process due to the Law of large numbers [116]. The theoretic properties of formulas (3-9) and (3-10) are investigated, when $\Delta t > 0$. First, Equation (3-13) is rewritten as

$$\hat{h}(t) = \frac{\int_t^{t+\Delta t} f(u)du}{\Delta t} \frac{1}{1-F(t)}. \tag{3-16}$$

Equation (3-16) implies that Equation (3-9) estimates the true hazard function values by dividing the average density $\left(\frac{\int_t^{t+\Delta t} f(u)du}{\Delta t}\right)$ over $1 - F(t)$, the system reliability value at time *t*. This implies that Equation (3-9) will underestimate the true hazard function values if the true density function (pdf) is decreasing over the interval $\Delta t$ and overestimate if the true pdf is increasing. Another way to show that Equation (3-9) may be underestimating the true $h_i$ values is to consider $\Delta t$ as a unit time interval, e.g. one hour, one day, or one year. Then, without loss of generality, the empirical hazard function is given as:

$$\hat{h}_i = \frac{N(t_i) - N(t_i + \Delta t)}{N(t_i)} \equiv \widehat{h1}_i.$$

Now Equation (3-14) is rewritten as

$$\hat{h}(t) = \frac{H(t+\Delta t) - H(t)}{\Delta t}, \tag{3-17}$$

where $H(t) = \int_0^t h(u)\mathrm{d}u = -\log(1 - F(t))$ is the cumulative hazard function. Equation (3-17) implies that Equation (3-10) calculates the average values of the true hazard function. Therefore, Equation (3-10) will underestimate the true hazard function during its decreasing stage and overestimate it during the true hazard function's increasing stage. If the true hazard function is constant, Equation (3-10) will give an unbiased estimation.

These theoretic properties of Equations (3-9) and (3-10) are verified by numeric calculation results as shown in Figure 3-12, from which a further analysis to what extent the bias of these two empirical hazards formulas is conducted. In Figure 3-12, plots on the left column are the densities of the specified distributions (i.e. exponential and Weibull); plots on the right column are the corresponding hazard function values calculated based on the specified parameters. For exponential distribution, the true hazards are calculated as:

$$h(t) = \lambda,$$

where $\lambda$ is a constant failure rate; For Weibull distribution, the true hazards are given as:

$$h(t) = \frac{\beta(t)^{\beta}}{\alpha^{\beta}},$$

where $\alpha$ and $\beta$ are the scale and shape parameters of the Weibull distribution.

In Figure 3-12, the top-down small triangle points indicates $\widehat{h1}_i$ and the small diamond points indicates $\widehat{h2}_i$, circle points are the true hazard function values connected by a fine solid line. The rate of the exponential distribution has been chosen to be 0.1 (plots in the first row); for Weibull distribution, shape = 3.5, scale = 60 for plots in row two; shape = 0.7, scale = 5 for plots in row three. The $\widehat{h1}_i$ values are calculated Equations (3-15); the $\widehat{h2}_i$ values are calculated using Equation (3-17).

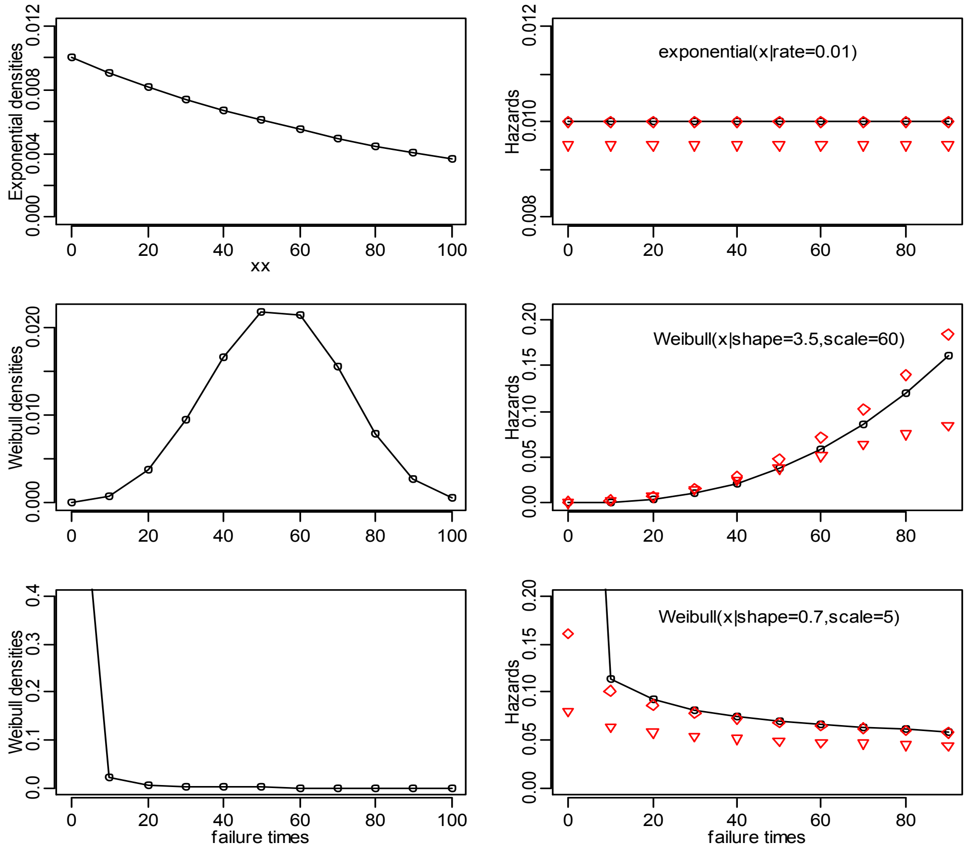



Figure 3-12 Investigation of the bias effects of the empirical hazard function values calculated using $\widehat{h1}_i$ and $\widehat{h2}_i$

Figure 3-12 shows that Equation (3-10) gives much less biased estimation of the true hazard function than Equation (3-9). In particular, Equation (3-9) underestimates the true hazard function values in most cases and the underestimation is substantial. On the other hand, the bias created by Equation (3-10) is minor or none, if the fitted model is an exponential distribution. Note that the extremely large underestimation of the very first point in the bottom plots of Figure 3-12 is because the true hazard value is positive infinity at $t = 0$ (in the case of a Weibull distribution with shape parameter less than one).

If $t + \Delta t \equiv t_2$ and $t \equiv t_1$, hence $\Delta t = t_2 - t_1$, Equation (3-6) and Equation (3-17) are identical. This is how Equation (3-10) related to AFR but Equation (3-9) does not have this direct connection.

As from Equation (3-11), the hazard function $h(t)$, also referred to as hazard rate at time $t$, is defined as a conditional density function, i.e. the ratio of probability density $f(t)$ over the reliability $1 - F(t)$ (a probability), which is not as intuitive to interpret as the concept of failure rate used in data analysis. The direct connection of

Equation (3-10) with the AFR fills the mental gap between the probability theory and data analysis.

Theoretically, the difference between formulas (3-9) and (3-10) is significant. However, in data analysis practice, the numeric calculation results from both formulas can be very close. As a standard mathematical result [116], it is known that, if $|x| \leq 2/3$, then

$$\log(1 + x) = x - \frac{x^2}{2} + \theta(x),$$

where $|\theta(x)| \leq |x|^3$. Therefore, it is straight forward to show that if $0 < x \leq 0.1$, the relative difference between $-\log(1 - x)$ and $x$ (i.e. $[-\log(1 - x) - x]/-\log(1 - x)$) is less than 6%.

A comparison of the estimation performances of Equations (3-9) and (3-10) to verify the theoretic results was conducted in the next sections using the simulation failure time data samples.

### 3.4.3 Comparison of empirical hazard function formulas using simulation samples

A random sample of an exponential distribution of sample size *n*=10000 is generated with the parameter specification rate = 0.1 (using random seed 101 for exact repeatability of the analysis results); A second random sample of a Weibull distribution of sample size *n* = 10000 is generated with the parameter specification: shape = 1.8 and scale = 30 (random seed = 101). Based on these two simulation random samples, the empirical hazard values $\widehat{h1}_i$ of Equation (3-9) and $\widehat{h2}_i$ of Equation (3-10) are calculated and compared with the true hazard function values to verify the theoretic results obtained from Section 3.4.2.

Figure 3-13 presents the simulation results of comparing the empirical hazard values $\widehat{h1}_i$ and $\widehat{h2}_i$ (invertical bars) against the true hazard function values (in circles connected by a fine solid line) based on the exponential distribution random sample. In calculating $\widehat{h1}_i$ and $\widehat{h2}_i$, the most important setting is to specify the number of intervals over the full sample data range. The specification of the number of intervals is equivalent to specify the length of $\Delta t$. Therefore, it is expected to see the larger of the number of intervals the better of the approximation of the $\widehat{h1}_i$ and $\widehat{h2}_i$ values to the true hazard values. In Figure 3-13, the empirical hazards in the top two panel plots are calculated using 20 intervals and in the bottom two panel plots the number of intervals is 50. As concluded in Section 3.4.2, it is expected to see $\widehat{h2}_i$ as an unbiased estimator of the true hazard function and that $\widehat{h1}_i$ will underestimate. The graph shows that $\widehat{h2}_i$ always performs better than $\widehat{h1}_i$, which is consistently underestimating the true hazards. The difference is much more significant when the number of intervals is small. It is also noticed that it is $\widehat{h1}_i$, which is much more sensitive to the number of intervals specification, while $\widehat{h2}_i$'s estimation results are very robust (i.e. almost not affected by the change of the number of intervals specification).

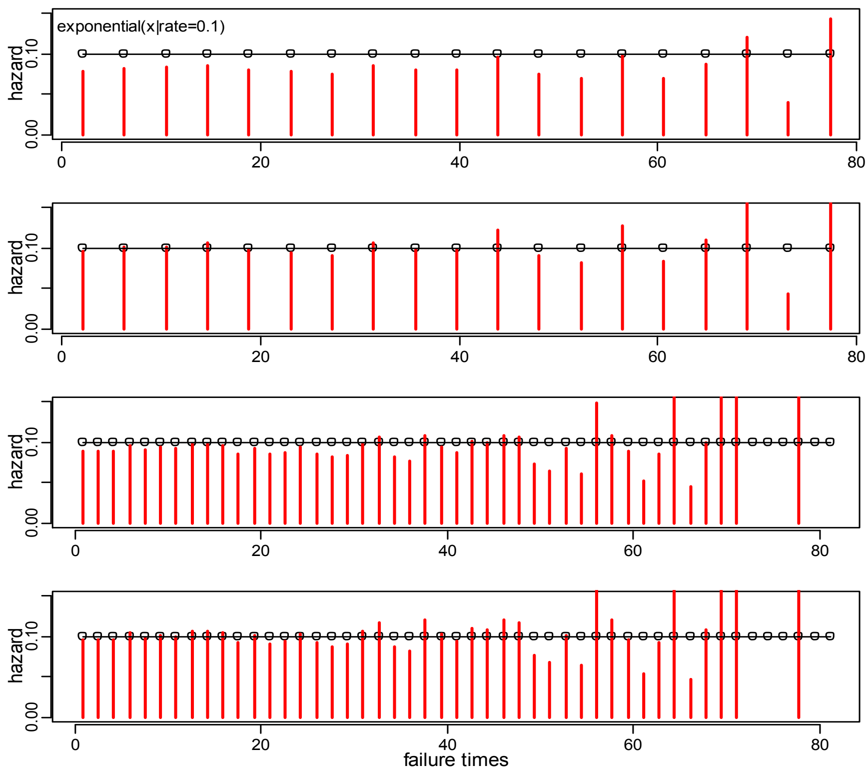



Figure 3-13 Empirical hazard function values calculated using $\widehat{h1}_i$ (the top and third panel plots) and $\widehat{h2}_i$(the second and bottom panel plots)

With this particular exponential distribution sample, the 99% quantile value is about 45 time units, which is spread over less than 60% of the full sample data range. Note that, for both $\widehat{h1}_i$ and $\widehat{h2}_i$, the estimates fluctuate wildly after the 99% quantile point because of the sparseness of observations over the upper part of the range interval. Actually, $\widehat{h2}_i$ will always have an infinite large hazard value for the last interval because it is imagined all components must fail in the end. On the other hand, $\widehat{h1}_i$ will always be equal to $1/\Delta t$ for the last interval; thus, empirical values of the very last interval should not be included. Therefore, only the estimates calculated from those sample observations are utilised, which are up to 99% quantile point.

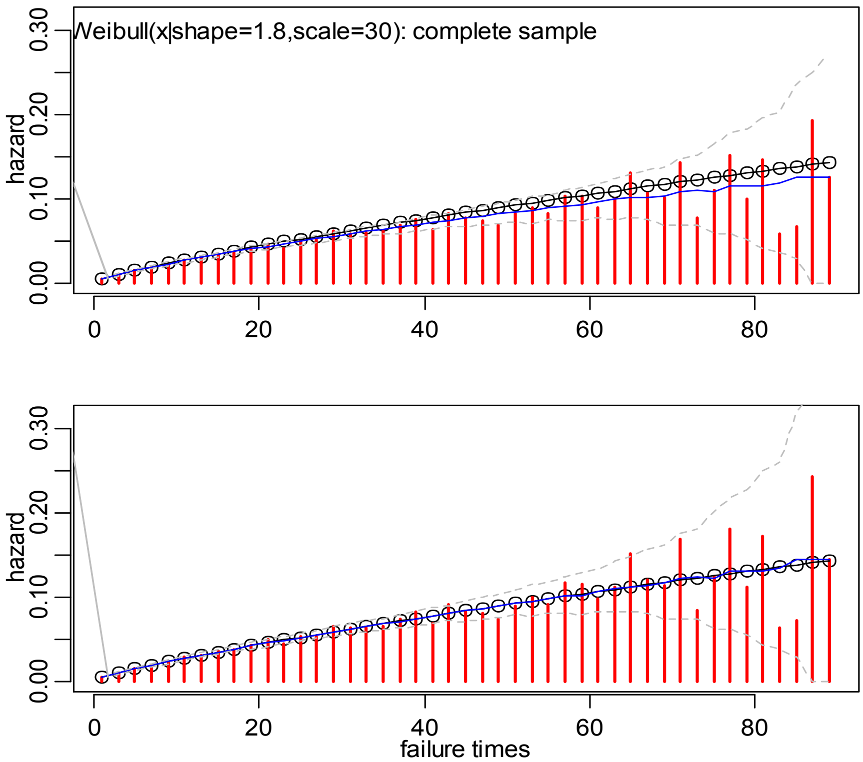



Figure 3-14 Empirical hazard function values calculated using $\widehat{h1}_i$ (top panel plot) and $\widehat{h2}_i$ (bottom panel plot)

Figure 3-14 examines the simulation results of comparing the empirical hazard values $\widehat{h1}_i$ (top panel) and $\widehat{h2}_i$ (bottom panel) against the true hazard function values based on a Weibull distribution random sample. Figure 3-14 follows the same drawing convention as in Figure 3-13, i.e. the empirical hazard values $\widehat{h1}_i$ and $\widehat{h2}_i$ are represented in vertical bars against the true hazard function values (in circles connected by a fine solid line). The number of intervals is chosen to be 45, i.e. $\Delta t$ = 2 time units. In addition, the approximate 95% confidence bands for $\widehat{h1}_i$and $\widehat{h2}_i$ values are constructed using the parametric bootstrap method [117]. Based on the Weibull distribution specification, 500 bootstrap samples (each of $n^* = 10000$) are generated and $\widehat{h1}_i$ and $\widehat{h2}_i$ are calculated for each of these bootstrap samples. The medians of empirical hazards are superimposed using a thick (in blue colour) solid line with the dashed lines (in grey colour) for the lower and upper limits respectively.

Based on the theoretic results obtained in Section 3.4.2, $\widehat{h1}_i$will overestimate when failure times are small and underestimate when failure times become larger; $\widehat{h2}_i$ will overestimate slightly the true hazards. In Figure 3-14, the overestimation effect of $\widehat{h1}_i$ and the overestimation effects of $\widehat{h2}_i$ are visually unidentifiable. In contrast, the underestimation effect of $\widehat{h1}_i$ is substantial. In addition, in this particular Weibull distribution sample, the 99% quantile point is at about 70 time units. In Figure 3-14, the superimposed confidence bands show how much the sampling variation can be over the upper part of the sample data range.

The results in this section have shown that $\widehat{h2}_i$ (defined in Equation (3-10)) is nothing but a finite approximation of AFR, whereas $\widehat{h1}_i$ (defined in Equation (3-9)) is a finite approximation of the instantaneous hazard rates. However, in their limiting forms, both $\widehat{h1}_i$and $\widehat{h2}_i$ converge to the true hazard function $h_i$.

For data analysis purposes, a rule of thumb for calculating empirical hazard function of continuous-time failure data may be summarised as: if the maximum failure rate over the time interval periods is less than 0.1, both $\widehat{h1}_i$ and $\widehat{h2}_i$ are good estimators of the true hazard function values. Most asset management reliability study cases should fall into this category. Otherwise, $\widehat{h2}_i$ should be used for calculating the empirical hazard function.

Note that both formulas are valid for randomly censored continuous-time failure data. In this section, it is necessary to concentrate on discussing the calculation of the complete failure time data using simulation samples.

## 3.5 HAZARD MODELLING FOR TRUNCATED LIFETIME DATA OF WATER PIPES

### 3.5.1 The real situation of lifetime data for water pipes

In reality, lifetime data for water pipes often contain a great proportion of truncated data. For a real water utility, the overwhelming majority of the water pipes may be right censored, because of a water pipe's long useful life, i.e. most of the pipes (more than 90%) may never have any repairs that have occurred during the observation period. The lifetime of water pipe segments showed different scenarios, which are illustrated in Figure 3-15.

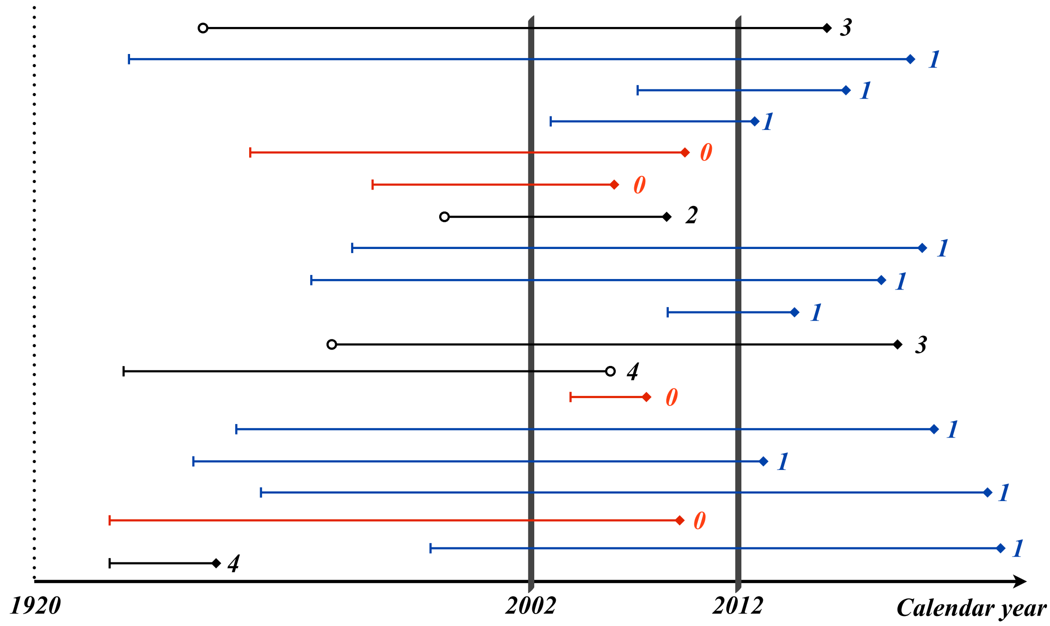



Figure 3-15 Schematic of lifetime distribution of water pipe segment in calendar time

In Figure 3-15, the following schema is used: the horizontal axis indicates the time line of calendar year, which starts from the year that the first pipe installed. Here, 1920 is set as an example. Each horizontal line indicates the lifetime of each pipe segment from its installation date to its repair date. Pipe segments represented by horizontal lines with little vertical bars on their left ends are for the known installation date cases; small circles representing the installation dates were missing. The small solid cube signs are marked on the right end of the line segment for indicating the repair date, again, a small circle representing the repair dates is missing. The two vertical lines with year 2002 and 2012 illustrate that the observation period is from 2002 to 2012. If the right ends of a pipe segment run beyond the 2012 line, this is the right-censored case. Therefore, in summary, pipe cases marked with ‘1’ are the right censored data; pipe cases marked with ‘0’ are the data with repair records; pipe cases marked with ‘2’ are the data with unknown installation date but repairs observed; pipe cases marked with ‘3’ are the right censored data but with unknown installation date; finally, pipe segment cases marked with ‘4’ are the missing value data of which researchers may not even be aware.

Given the fact that the number of data with unknown installation dates is so few, these data are treated as missing value data and exclude them before starting the empirical hazards calculation. In order to calculate the age-specific empirical hazard values, firstly the observations are needed to be synchronised. Note also, even with those pipes which have been repaired, the pipes still exist so that they must be included as part of the total length pipes in operation. Figure 3-16 gives the schematic illustration of the situation.

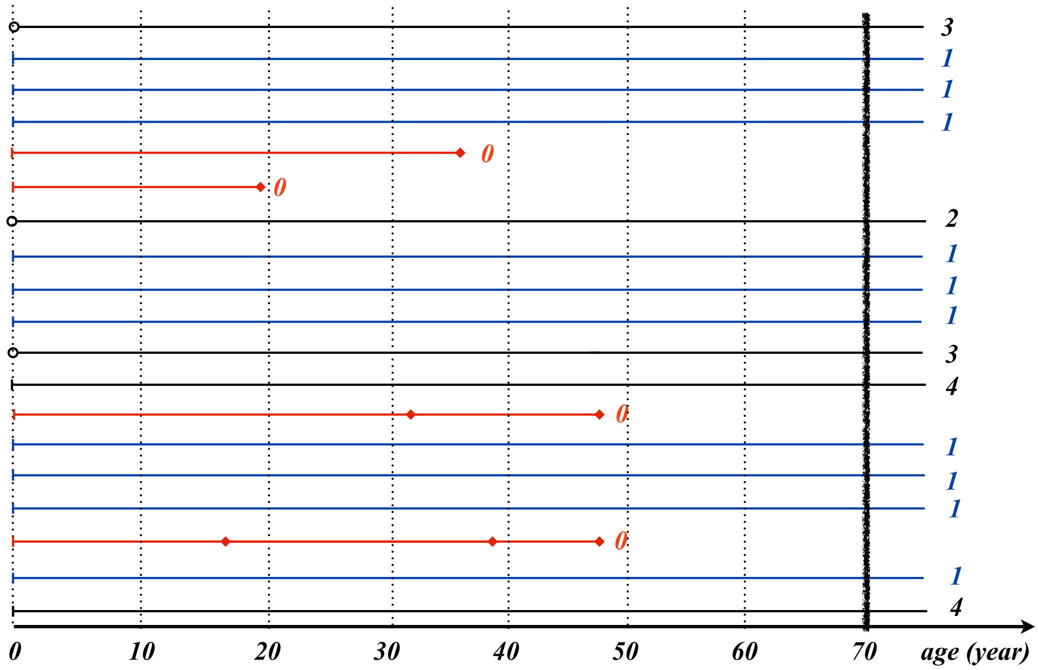



Figure 3-16 Schematic of lifetime distribution of water pipes (age-specific)

In Figure 3-16 the horizontal axis indicates the time line of age in year, which starts from "0". Each horizontal line indicates the lifetime of each pipe from age "0" to the age when it is repaired. The vertical line with age 70 illustrates the observation period for the longest age of pipes. For pipes marked with "1", this indicates the right censored situation, where their ages are longer than the longest observed age of pipes. The pipes marked with "2" and "3" do not retain any information of their installation data; therefore, their ages are unknown. It is impossible to calculate the empirical hazard based on age, therefore, these two types of pipes are treated as invalid data. The pipes marked with "0" are the pipes with failure/repair history records.

Pipes marked with "4" cannot be observed and it is impossible to know how many pipes are in this scenario and which pipe falls into this scenario. Therefore, in the interval truncated observation, pipes in scenario "4" can only be treated as the pipes in scenario "1". In Section 3.4.1, $r_i$ is the length of pipe segments at risk at $t_i$, $r_i \equiv N(t_i)$. If pipes in scenario "4" are treated as pipes in scenario "1", $r_i$ will be greater than its original values. Therefore, using Equation (3-9) or Equation (3-10), the calculated empirical hazard will underestimate the true hazard value.

In the next section, a modified empirical hazard function to deal with the interval truncated lifetime data is developed in order to reduce the underestimation of hazard.

### 3.5.2 Empirical hazard function for interval truncated lifetime data

In section 3.4.2, two empirical hazard functions were introduced in Equation (3-9) and Equation (3-10) given as:

$$\hat{h}_i = \frac{N(t_i)-N(t_i+\Delta t)}{\Delta t \cdot N(t_i)} = \frac{1}{\Delta t}\frac{d_i}{r_i} \equiv \widehat{h1}_i,$$

and

$$\hat{h}_i = -\frac{1}{\Delta t}\log\left[1-\frac{N(t_i)-N(t_i+\Delta t)}{N(t_i)}\right] = -\frac{1}{\Delta t}\log\left(1-\frac{d_i}{r_i}\right) \equiv \widehat{h2}_i.$$

$d_i$ indicates the length of repaired pipe in the interval between time instant $t_i$ and $t_{i+1}$, $i = 1,2,\ldots$, where $d_i = N(t_i) - N(t_{i+1})$.

$$r_i \equiv N(t_i) \ , \qquad (3\text{-}18)$$

is the length of pipe segments at risk at $t_i$. $N(t_i)$ and $N(t_{i+1})$ are the length of pipes which are functional at time $t_i$ and time $t_{i+1}$, respectively, where $t_i$ and $t_{i+1}$ indicate a pipe's age in year units.

For the interval truncated lifetime data, a truncated time interval is given as $(L_i, R_i]$. The length of pipes' survival at time $L_i$ and $R_i$ are given as $N(L_i)$ and $N(R_i)$, respectively. The length of pipes repaired in the time interval $(L_i, R_i]$ can be denoted as $N_{LR}$, which can be calculated by $N_{LR} = N(R_i) - N(L_i)$.

As introduced before, water pipe as a linear asset can be treated as a number of unit-length segments, and each repair is replacing the pipe segment. Compared with the length of pipe, the length of each segment is far smaller than the whole pipe, therefore, the condition of the whole pipe after each repair can still remain "as bad as old", even if the condition of each repaired segment is "as good as new". Therefore, an assumption is made that the condition of these repaired pipe segments in unit-length $N_{LR}$ can be treated "as good as new". These repaired pipe segments are treated as additional new pipe segments, and a new asset table is created for the new pipe segments. Therefore the new pipe length at time $t_i$ is given by $N_{new}(t_i)$.

In the truncated time interval $(L_i, R_i]$, $r_i$ is given as:

$$r_i = N(t_i) - N(L_i) + N_{new}(t_i), \tag{3-19}$$

which indicates that the $r_i$ equals to the length of pipes survival at time $t_i, N(t_i)$, minus the length of pipes' survival at time $L_i$, $N(L_i)$, plus the length of new pipe segments at time $t_i$, $N_{new}(t_i)$, where time $t_i$ indicates a pipe's age in year units. Therefore, empirical hazard in truncated time interval $(L_i, R_i]$ can be calculated using Equation (3-10) and Equation (3-19).

### 3.5.3 Monte Carlo simulation based on real lifetime data for water pipes

This section describes a Monte Carlo simulation framework, which was developed to verify the proposed hazard model with truncated lifetime data. It is contributed by team efforts from CIEAM[118]. The core simulation program is able to generate failure data samples, which represents realistic censorship patterns as observed in real-world data, providing a controlled test bed for the development and evaluation of failure models.

The Monte Carlo simulation framework includes six steps:

*Step 1: Creation of the Test-bed Asset data file*

For the raw real life data set, any data records, which are incomplete, such as the installation dates are missing or the pipe length information is missing, are deleted. In addition, based on the assumption that one metre is the unit-length of a segment for each pipe, all pipes which have a total length less than one metre were also excluded. Then a test-bed asset data file is created with the values of a pipe's ID, length, and installation date included;

*Step 2: Specification of simulation parameters*

Several simulation parameters are specified, which include (1) the start date and end date of the observation period, where the specified start date and end date should be in a reasonable range, and the specified end date should be later than the start date; (2) the parameters of the piece-wise hazard model are set, which include wear-out point (*tw*), exponential, shape and scale parameters;

*Step 3: Discretisation of pipe length*

Each pipe is broken down into a number of independent unit-length (one-metre) segments for modelling purposes, assuming that all the one-metre segments have the same failure rate.

*Step 4: Generation of lifetime distribution before the wear-out point (tw)*

Based on the input value of the exponential parameter, lifetime for each segment is generated. If the lifetime is equal to or smaller than the value of *tw*, the lifetime value will be saved for that segment. For those segments with lifetimes larger than the values of *tw*, the lifetimes are temporarily saved and the simulation moves on to Step 5.

*Step 5: Generation lifetime distribution after the wear-out point (tw)*

For those segments temporarily saved in Step 4, new lifetimes were generated based on the input values of the shape and scale parameters. The new lifetime is compared with the temporarily saved lifetime for each segment, and the smaller one is saved as the final lifetime.

*Step 6: Selection of segments for their failure date in the observation period*

The age-specified lifetimes were transferred to the time scales of calendar years based on the installation dates in the test-bed asset data file. Then, the segments, whose lifetimes are located in the observation period (defined by the start and end date), are selected and saved in a failure record file. The procedure will be terminated if all pipes are treated, then the saved failure record file is the simulated failure record for the whole water pipe network; otherwise, the simulation moves back to Step 3.

### 3.5.4 Validation of the proposed empirical hazard function

In this section, the test-bed sample data based on the Monte Carlo simulation is implemented to test and validate the proposed empirical hazard function of truncated lifetime data. The truncation period is determined by the start date and end date in the Monte Carlo simulation. The improvements based on Equation (3-19) on the installation data distribution and pipe length distribution of water pipes are conducted and analysed with the following examples.

***Example 1:***

In Example 1, parameters are shown in Table 3-2, where $\lambda$ is a constant failure rate, $\xi$ indicates the start time, $\alpha$ and $\beta$ are the scale and shape parameters of the

Weibull distribution in Equation (3-1). The "Observation period" indicates the observation starting at 01/07/2002 and finishing at 30/06/2012.

Table 3-2 Parameters for Example 1

| $\xi$ | $\lambda$ | $\beta$ | $\alpha$ | Observation period |
|---|---|---|---|---|
| 15 | 0.0001 | 1.5 | 370 | 01/07/2002 to 30/06/2012 |

In Figure 3-17, the top chart shows the hazards with age in years based on Equation (3-18), the red bar shows the empirical hazard, and the blue solid line indicates the true hazard; The meddle chart indicates the length distribution in kilometres and the bottom chart shows number of repairs with age in years.

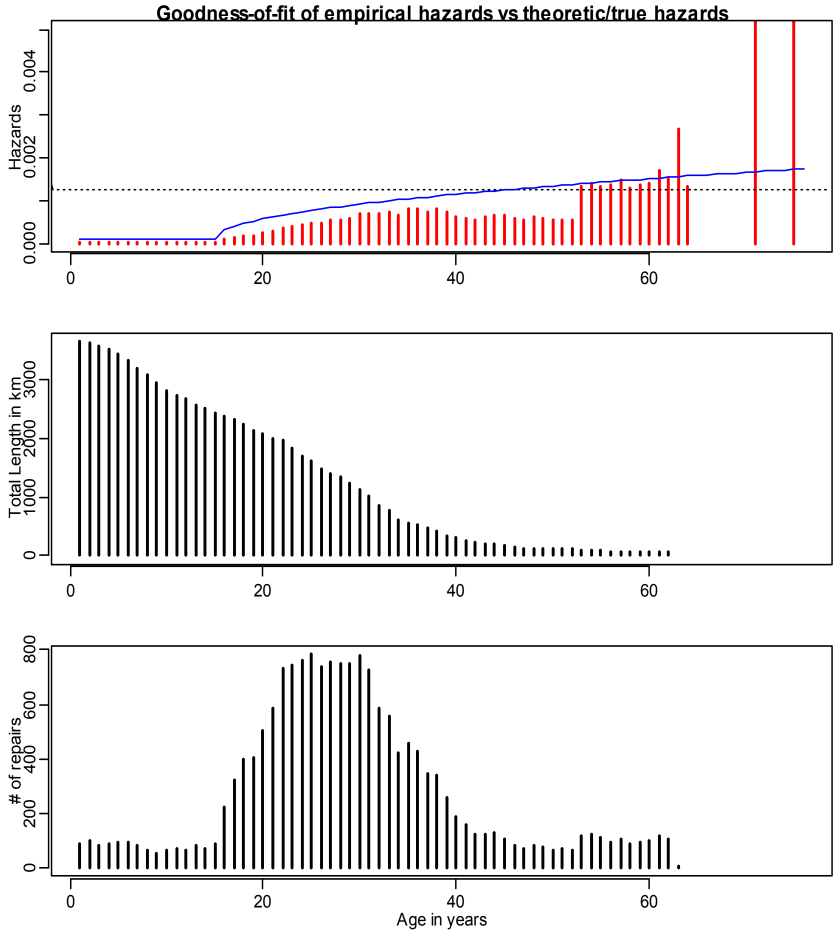



Figure 3-17 The goodness-of-fit of empirical hazards vs. the true hazard based on Equation (3-18)

Figure 3-18 shows the hazards with age in years based on Equation (3-19). The hazard plot in Figure 3-18 is almost a perfect fit compared with the hazard plot in Figure 3-17, which shows a fundamental improvement over the old way of calculating the empirical hazards.

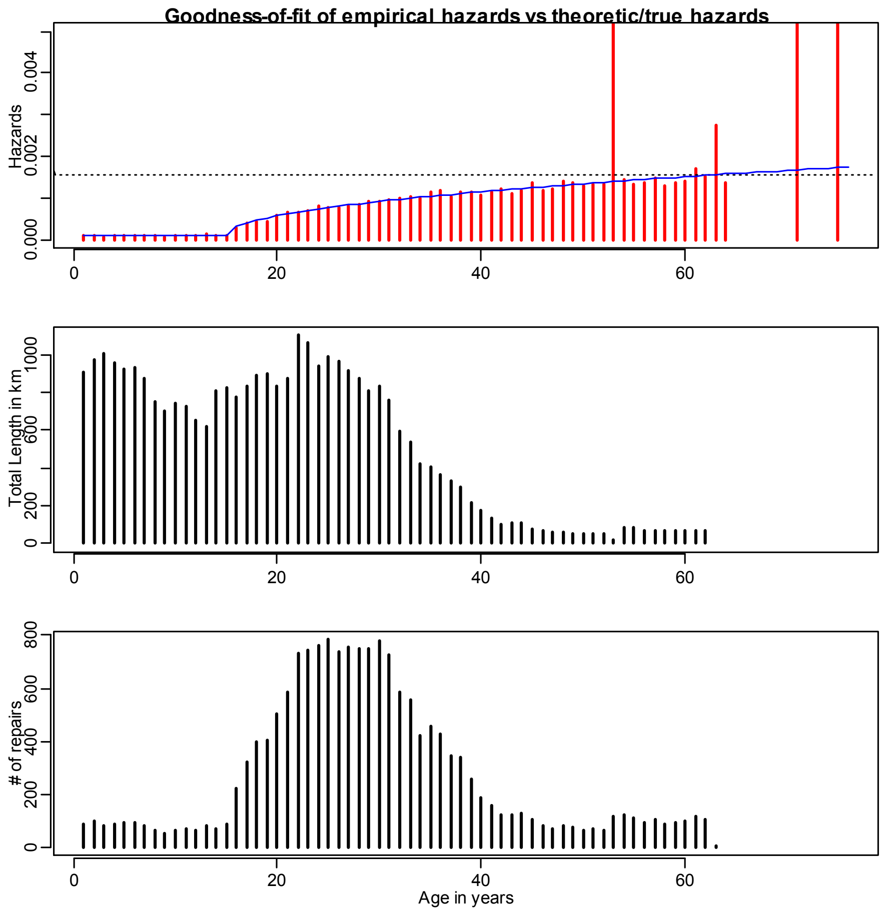



Figure 3-18 The goodness-of-fit of empirical hazards vs. the true hazard based on Equation (3-19)

The difference between the middle panel plots, shows the difference of the cumulative total length plots calculated based on Equation (3-18) and (3-19). In Figure 3-17, it is a monotonic decreasing profile because it is the cumulative curve and all pipelines are included, while in Figure 3-18, the pattern is no longer monotonic decreasing, because it only includes those pipe segments within the observation period.

***Example 2:***

Example 2 is a simulation of hazard function for an extreme situation, where the repaired length of pipes has occupied a large proportion of the total length of pipes during the observation period.

In Example 2, the parameters are shown in Table 3-3, where "Situation A" and "Situation B" have a different observation period.

Table 3-3 Parameters for Example 2

| $\xi$ | $\lambda$ | $\beta$ | $\alpha$ | Situation A | Situation B |
|---|---|---|---|---|---|
| 10 | 0.0001 | 1.1 | 49 | Earliest installed date to 30/06/2012 | 01/07/2002 to 30/06/2012 |

Figure 3-19 and Figure 3-20 are in the same structure of Figure 3-17 in that the top chart shows the hazards with age in years, the middle chart shows the total length distribution in kilometres, and the bottom chart shows the number of repairs with age in years.

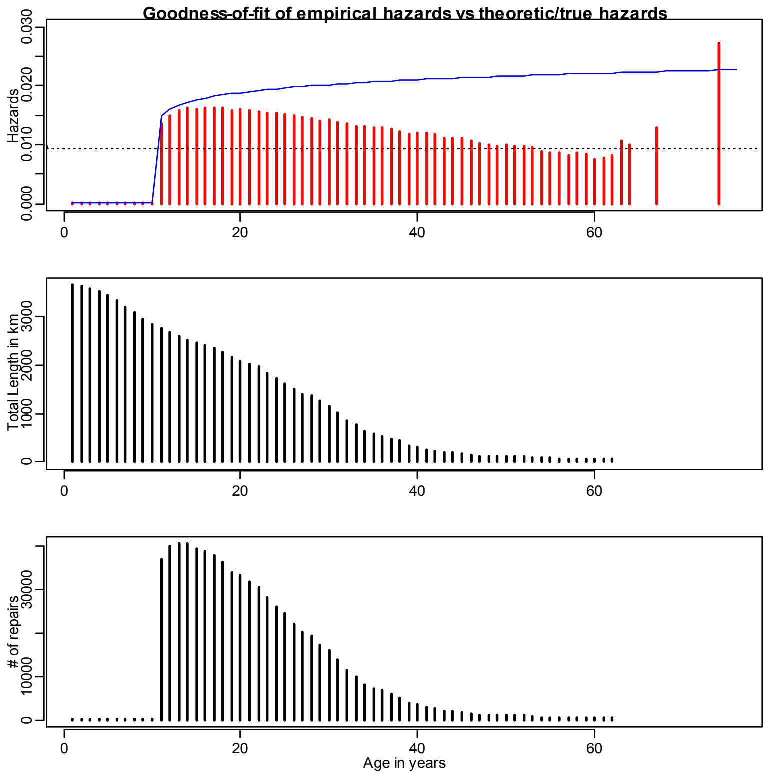



Figure 3-19 The goodness-of-fit of empirical hazards vs. the true hazard in Situation A based on Equation (3-18)

The hazard plot in Figure 3-20 is almost a perfect fit compared with the hazard plot in Figure 3-19, which shows a fundamental improvement over the old way of calculating the empirical hazards. The difference between the middle panel plots shows the difference of the cumulative total length plots calculated based on Equation (3-18) and (3-19).

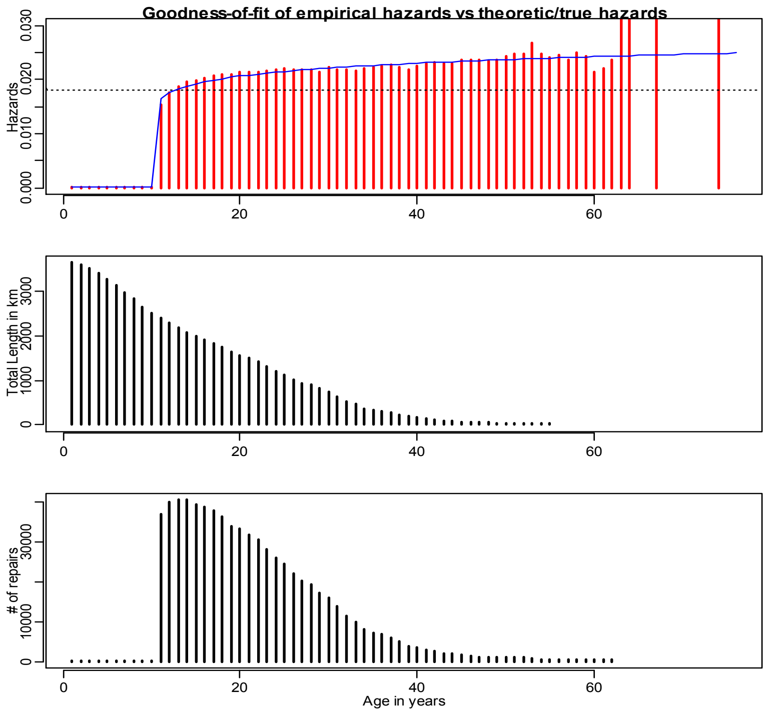



Figure 3-20 The goodness-of-fit of empirical hazards vs. the true hazard in Situation A based on Equation (3-19)

However, calculated empirical hazards for Situation B (blue bar) shows great underestimation for the true hazards (light blue solid line), especially in old ages, which is shown in Figure 3-21. This underestimation was caused by the extreme large proportion of failures (about 20% of the total length failed, i.e. 700,000 out of 3.6 million metres). In this case, the proposed empirical hazard function reaches its limitation. Example 3 may give some ideas about to what extent the Equation (3-19) can still produce a satisfactory result.

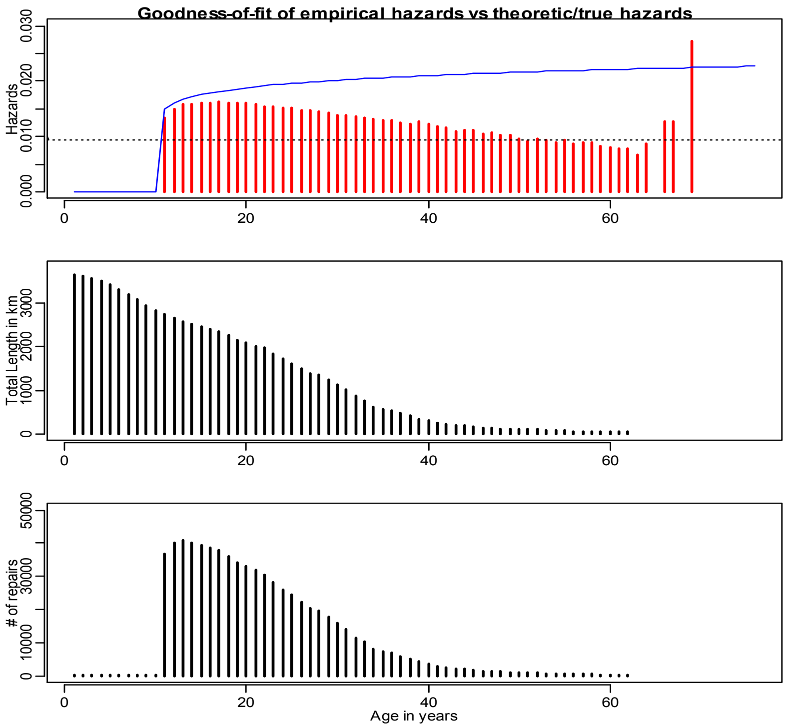



Figure 3-21 The goodness-of-fit of empirical hazards vs. the true hazard in Situation B based on Equation (3-19)

***Example 3:***

Example 3 gives some ideas about to what extent the Equation (3-19) can still produce a satisfactory result, where the repaired length of pipes occupied a large proportion of the total length of pipes during the observation period. In Example 3, the parameters are shown in Table 3-4.

Table 3-4 Parameters for Example 3

| $\xi$ | $\lambda$ | $\beta$ | $\alpha$ | Observation period |
|---|---|---|---|---|
| 10 | 0.0001 | 1.15 | 200 | 01/07/2002 to 30/06/2012 |

The Figure 3-22 and Figure 3-23 are in the same structure of Figure 3-17.

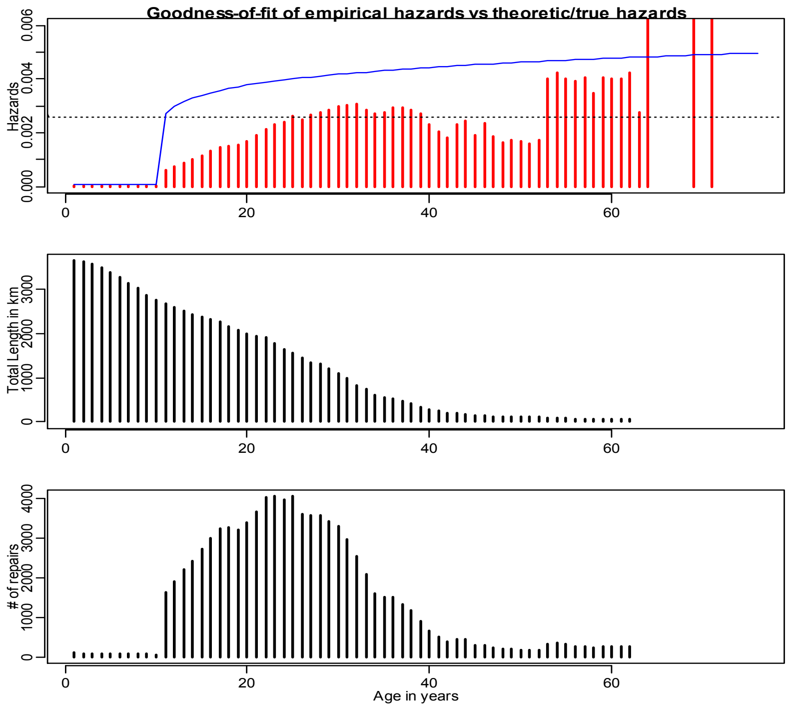



Figure 3-22 The goodness-of-fit of empirical hazards vs. the true hazard based on Equation (3-18)

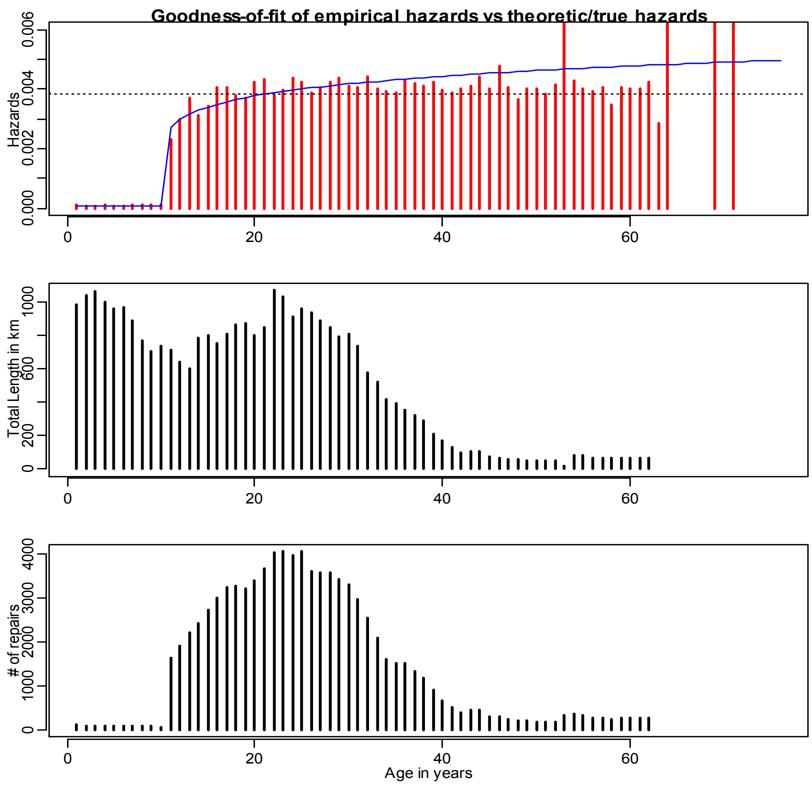



Figure 3-23 The goodness-of-fit of empirical hazards vs. the true hazard based on Equation (3-19)

In Example 3, the number of failures generated by the simulation is about 88,000. In practice, this great number of failures is a pretty 'bad' case, which is hardly happened in real life. Compared with the hazard plots in Figure 3-22 and Figure 3-23, Equation (3-19) still can handle well, compared with Equation (3-18). Therefore, the calculated empirical hazards based on Equation (3-10) and (3-19) are good estimations of the true hazards based on the simulation experiments, which can be applied for most of the failure scenarios for water pipes.

### 3.5.5 Hazard distribution fitting method for the piece-wise hazard model

Parameters of the piece-wise hazard model can be estimated by non-linear regression. However, there is a limitation that the wear-out point needs to be estimated by expert knowledge; Therefore, in this section, a hazard distribution fitting method is developed.

To automatically estimate the optimal wear-out point ($tw$), an equation to calculate the error between the empirical hazard and the fitted hazard of a given $tw$ is given as:

$$R_{ef} = \sum_{t=1}^{\max(t)} \left| \hat{h}(t) - h_{fit}(t, tw) \right|, \qquad (3\text{-}20)$$

where $\hat{h}(t)$ indicates the empirical hazard at age *t*, and $h_{fit}(t, tw)$ indicates the fitted hazard at age *t* with a value of $tw$. $h_{fit}(t, tw)$ is calculated by the non-linear regression introduced in Section 3.2, based on a given $tw$. $tw = 1,2, \dots \max(t)$, where the $\max(t)$ is normally lower than 100.

In the fitting method, $tw$ is given from 1 to the $\max(t)$. For each given $tw$, the non-linear regression is used to estimate the parameters of $\lambda$, $\beta$, and $\alpha$ in Equation (3-1). Then the objective is to find the optimal $tw$, which let the $R_{ef}$ have a minimum value, so that the optimal wear-out point ($tw$) is estimated.

This fitting method is verified by the simulation samples in Example 1 applied in Section 3.5.4. In Figure 3-24, the blue line is the true hazard function values; the vertical bars are the medians of the empirical hazard function values calculated from 100 bootstrap samples; the two black dashed lines are the approximate 95% confidence band; the red circle points are the medians of the fitted hazard values connected by a fine solid line, which is calculated from 100 bootstrap samples; the two purple dashed lines are the approximate 95% confidence band for the fitted hazard values.

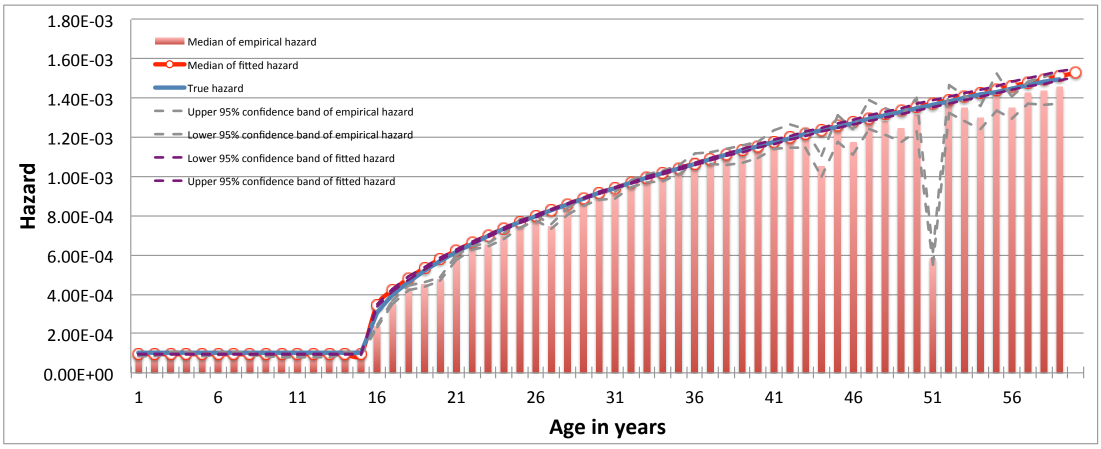



Figure 3-24 The goodness-of-fit of fitted hazards vs. the empirical hazard based of Example 1

Table 3-5 Parameters estimation for Example 1

| | $\xi$ | $\lambda$ | $\beta$ | $\alpha$ |
|---|---|---|---|---|
| True | 15 | 0.0001 | 1.5 | 370 |
| Estimated | 15 | 0.000097 | 1.51 | 375 |

From Figure 3-24, it is shown that in Example 1, the fitted hazard curve is nearly a perfect estimation for the empirical hazard; Table 3-5 listed the parameters estimated by the model. The wear-out point $\xi$ can be automatically calculated, and it is equal to the true wear-out point.

## 3.6 PROCEDURE OF THE IMPROVED HAZARD MODELLING METHOD FOR WATER PIPES

The water pipes failure prediction using the improved hazard modelling method introduced in this chapter has a clear and straightforward procedure to analyse the asset and failure data, which is described below:

Step 1: Choosing an appropriate hazard model

For most of the linear assets, a four-parameter piece-wise hazard model is recommended, for the reason that it can deal with discretised linear assets, which was introduced in Section 3.2.

Step 2: Statistical grouping analysis

Pipe data should be partitioned based on their characteristic features using the statistical grouping algorithm. The four-step grouping procedure should be followed for partitioning pipes, which was developed in Section 3.3. Then the final groups and the grouping criteria can be acquired.

Step 3: Choosing empirical hazard function

The empirical hazard function of Equation (3-10) is recommended for all circumstances. However, if the failure rate is less than 0.1, both Equation (3-9) and Equation (3-10) will be appropriate for calculating empirical hazard.

Step 4: Calculating empirical hazard values based on the modified empirical hazard model

For real life data, Equation (3-19) combined with Equation (3-10) is recommended for calculating empirical hazard values in order to reduce the underestimation effects.

Step 5: Estimating the model parameters based on empirical hazard values

To estimate the model parameters, MLE or regression methods can be used based on the hazard models. For the piece-wise hazard model, the non-linear regression method can be applied to calculate the four parameters.

## 3.7 SUMMARY

This chapter described an improved hazard modelling method for water pipes. The development of this model includes three components. The first component is a statistical grouping algorithm using a four-step procedure, which combines age specific material analysis, length related pre-grouping, regression tree analysis, and grouping criteria adjustment based on knowledge rules. The result of a case study showed that, by applying this procedure, pipe data can be partitioned into more homogeneous groups, and sufficient sample size of failure data for each group can be guaranteed.

The second component is a comparison study of two commonly used empirical hazard formulas $\widehat{h1}_i$ and $\widehat{h2}_i$ (Equations (3-9) and (3-10)) for investigating their differences of application impacts. The differences were tested using simulation samples from exponential and Weibull distributions. The investigation of the empirical hazard formulas for linear assets draws the following conclusions: (1) $\widehat{h1}_i$ is a finite approximation of the instantaneous failure rate, and it underestimates the true hazard function values in most cases and the underestimation is substantial; and the underestimation of $\widehat{h1}_i$ is much more sensitive to the change of time interval $\Delta t$; (2) $\widehat{h2}_i$ is a finite approximation of average failure rate (AFR), and it gives a much less biased estimation of the true hazard function than $\widehat{h1}_i$; $\widehat{h2}_i$ is almost not affected by the change of time interval $\Delta t$. (3) For calculating empirical hazard function of continuous-time failure data, if the maximum failure rate over the time interval periods is less than 0.1, both formulas are good estimators of the true hazard function values. Otherwise, $\widehat{h2}_i$ has more accuracy of result than $\widehat{h1}_i$ for calculating the empirical hazard function.

The third component is a modified empirical hazard function to deal with the underestimation effects due to interval truncated lifetime data by considering three types of pipe segments: survived segments, repaired segments and new segments. A Monte Carlo simulation framework has been developed in order to generate test-bed sample data sets in terms of the main features of the real data of a water utility. Based on the simulation results, the modified empirical hazard function can effectively reduce the underestimation effects caused by the interval truncation of lifetime data.

By applying the improved hazard modelling method for water pipe reliability analysis, the hazard curves between groups can be clearly distinctive from each other; and the underestimation effects caused by interval truncated lifetime data can be reduced; hence, more accurate hazard prediction results for each group of pipes can be calculated.

# Chapter 4: Optimization Model of Group Replacement Schedules for Water Pipelines

## 4.1 INTRODUCTION

Replacement of water pipeline is crucial to water utilities due to the deterioration of water pipes, especially those that are aged. Not only does replacement contribute to the service with quality, but also enriches all the company experience surrounding the service provided[119]. Huge investment pressures of water pipe maintenance has led to the improvements of replacement efficiency and cost effectiveness. Researchers have provided various replacement decision support models [6, 8, 11, 12].

In current practice, replacement activities are usually scheduled into groups manually. However, this practice fails to provide an optimal solution because it relies on users' experiences. Optimal group scheduling needs to take into consideration of multiple criteria such as costs, impact of service interruptions, pipe specifications, the type of technology employed and geographical information. However, replacement group scheduling for individual water pipes considering multiple criteria has so far not received enough attention in literature.

To improve the existing replacement scheduling, an innovative decision model, Replacement Decision Optimization Model for Group Scheduling (RDOM-GS), is proposed in this chapter. This model provides planners unambiguous information for optimizing group replacement scheduling for groups of water pipelines. This model enables planners to develop group replacement schedules against three criteria: shortest geographic distance, maximum replacement equipment utilization, and minimum service interruption. The RDOM-GS integrates cost analysis, service interruption analysis, and optimization analysis to deliver schedules that limit service interruptions and minimize total life-cycle cost.

The rest of the chapter starts with water pipeline maintenance with the economics of repair and replacement in Section 4.2. Then, in Section 4.3, cost functions for water pipeline repair and replacement are introduced and developed, based on the hazard model developed in Chapter 3. In Section 4.4, replacement group scheduling criteria are introduced, followed by a judgment matrix and three integrated models for replacement group scheduling. A new replacement cost function for group scheduling is developed in Section 4.5, followed by a customer service interruption model in Section 4.6. The objectives and constrains for RDOM-GS are summarized in Section 4.7. Finally, the structure of the RDOM-GS is summarised in Section 4.8.

## 4.2 MAINTENANCE ON WATER PIPELINES

### 4.2.1 Repair and replacement of water pipeline

Maintenance plays an essential role in asset management to improve the reliability of system. There are two basic categories of maintenance [33], corrective maintenance and preventive maintenance. Corrective maintenance follows in-service failures to restore the system to its operational state through corrective action, and nothing is done before the system fails, while preventive maintenance is performed at an interval of time, to control the deterioration process, which leads to the failure of a system, even if the system is still working satisfactorily.

The maintenance for water pipelines can be described as two categories:

1. *Repair* (corrective maintenance)

   In practice, corrective maintenance of water pipes is carried out after a failure (break/rupture/leak). A small segment of pipe near a failure rather than the whole pipe is replaced. Corrective maintenance is considered as a 'repair' in this thesis.

2. *Replacement* (predictive maintenance)

   To improve the network reliability and to prevent the occurrence of failures, aged water pipes with high probability of failures are replaced by all-new ones (the whole pipes, not only a number of pipe segments). The condition of the replaced pipe is as "good as new". New types of material might alternate the old ones, for example, AC pipes are often substituted by PVC pipes and CICL pipes are often substituted by DICL pipes. Several reasons result in the material alternation: (1) the improvement of durability in operation, (2) low in price, and (3) easy to install and transport, (4) availability of the pipe material.

For linear assets, Sun [120] made some assumptions for repair and replacement. Based on his assumptions, in this research, a number of assumptions are made for repair and replacement of water pipelines:

The *repair* pre-supposes a number of conditions:

a) Each repair is conducted after and only after each failure;

b) Each repair only treats one segment of pipes, which is assumed to be one metre long;

c) The duration of repair after each failure is assumed to have deterministic values, which is determined by expert knowledge;

d) After each repair, the segment of pipe is restored to an "as good as new" condition, and this repaired segment will function until the whole pipe is replaced;

e) Since for each repair, only one segment is replaced in the whole pipe, the condition of the whole pipe is assumed to be "as bad as old".

The *replacement* pre-supposes four conditions as well:

a) Replacement means renewal of the whole pipe and the condition of the replaced pipe becomes "as good as new";

b) Replacement activities are scheduled in a planning period *T* (planning horizon). *T* in this research is much smaller than the average life of a water pipe (normally more than 100 years), therefore, it is assumed that one pipe can only be replaced one time during the planning period *T*;

### 4.2.2 Economics of pipeline failure and pipeline replacement

Water pipeline failure is associated with undesirable consequences, which may be interpreted in economic terms. These economic terms include monetary and non-monetary items. The classification is shown below:

1. Monetary items of water pipeline failure include direct monetary cost, and indirect monetary cost:

   Direct monetary cost indicates the cost that is directly caused by the water pipeline failure, for example, the loss of fresh water, the material for repairing the failure.

Indirect monetary cost indicates the loss indirectly caused by pipeline failure, for example, labour cost of repair, property damages (due to flood), possible penalty due to service interruption.

2. Non-monetary items of water pipeline failure indicate the items, which cannot be interpreted into monetary value, but the effects of which couldn't be ignored.

   The most important one in economic terms is the effect of service interruption. If a pipe ruptures, the pipe will need to be isolated from the rest of the water network to allow a repair. Those customers, whose services are interrupted, will lose water supply. Other non-monetary items include blocking roads, the loss of reputation, environmental contamination.

   Some non-monetary items could be translated as monetary equivalent items, for example, Zhang [121] established a monetary equivalent relationship between service interruption and the cost of substitute bottles of water.

The cost of water pipeline replacement, which is associated with planned activities, contains monetary and non-monetary items as well. The monetary cost includes cost of manpower, cost of material and spares, cost of tools and equipment needed for carrying out maintenance actions [107]. The non-monetary cost is similar to the cost of failure that contains service interruption, blocking road, environmental contamination.

Generally, increasing the frequency of replacement can reduce the frequency of failure and improve the network reliability, so as to decrease the repair cost. However, the increasing frequency of replacement leads to an increase in the total replacement cost. Reducing replacement frequency often leads to an increase in repair costs, because longer replacement intervals normally mean more failures. It is almost impossible to minimize all these costs simultaneously. Similarly with the monetary items, the more frequent the replacement is, the more interruption is caused by replacement, but less is the undesirable interruption due to water pipeline failures. Therefore, it is reasonable to find an optimal point to balance both replacement and repair activities.

## 4.3 COST FUNCTIONS FOR WATER PIPELINE REPLACEMENT PLANNING

### 4.3.1 Age specified cost functions of water pipeline failure

A practical approach to deciding the optimal replacement time for an economizer tubing system was developed by Sun and Lin [120], their approach considered the failure rate of the tubing system to deal with repair cost, replacement cost and production loss. The economizer tubing system contains tubes with a group of segments, which are treated as linear assets. As described previously, water pipelines are linear assets, but they have longer lifetime, and are distributed in a very large area, therefore, optimal replacement time for water pipeline can be calculated based on modified cost approaches.

Failure cost increases with the increasing failure frequency or the probability of failure if the replacement is delayed, due to the aging and deterioration of a pipe. The Failure cost rate based on the probability of failure in age $\tau$ for each pipe is given as:

$$R_{fail} = \frac{C_{fail} \cdot Nseg \cdot \int_0^{\tau} f_{crp}(\tau) d\tau}{\tau}, \tag{4-1}$$

where *Nseg* is the number of segments repaired of pipe $i$, $C_{fail}$ stands for the cost incurred due to a pipe segment failure, and $f_{crp}(\tau)$ indicates an age specific failure probability of pipe $i$, which can be calculated using the improved hazard model proposed in Chapter 3.

The failure cost function $C_{fail}$ presented in this research focuses on unit operations, where one pipe repair activity by trench is regarded as one unit. Based on the definition of repair, each repair is only for a one-metre pipe segment, therefore, the repair cost is not related to the pipe length.

There are some factors, which impact the repair cost. These factors include the diameter of the repaired pipe and the pipe's material. Practically, the larger the diameter of pipe, the larger and deeper the trench is necessary for digging, therefore, the more costly the repair is. Moreover, there is no apparent relationship between repair cost and material. Therefore, in this research, $C_{fail}$ is assumed to follow the following non-linear pattern:

$$C_{fail} = a + b \cdot {D_i}^c, \tag{4-2}$$

where $D_i$ is the diameter of pipe $i$, and $a$, $b$, and $c$ are the coefficients, which can be estimated using the nonlinear regression. The details are introduced in Section 6.4.1.

Considering the replacement activity at age $\tau^*$, after each replacement activity, a pipe (all segments) is replaced as an all-new one, and the reliability of the new pipe is as "good as new", therefore, the failure cost rate based on the probability of failure will be reduced to the statue as new pipe. Figure 4-1 shows the failure cost rate considering the replacement at age $\tau^*$. The repair cost during age $\tau$ is the summation of the cost from 0 to $\tau$:

$$C_{fail,\tau^*} = C_{fail} \cdot Nseg \cdot \left(\int_0^{\tau^*} f_{crp}(\tau)d\tau + \int_{\tau^*}^{\tau} f_{crp}(\tau - \tau^*)d\tau\right), \tag{4-3}$$

which is the sum of the area with slashes showed in Figure 4-1. The lower limit of the repair cost rate function (dash line in figure 4-1) indicates the repair cost rate is larger than 0, and considering the development of new maintenance technologies, the repair cost rate of new pipes will remain a slight decreasing trend.

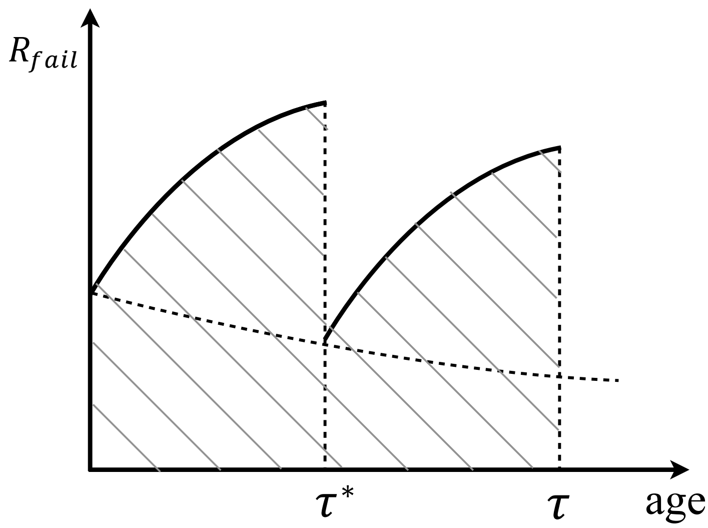



Figure 4-1 Failure cost rate with replacement at $\tau$

### 4.3.2 Function of total cost in a planning period *T*

Replacement decision-making is usually conducted for a planning period *T*, for the reason that replacement budgets are usually produced for one fixed period, for example, 20 years. Water pipeline is a long life asset, its age can last over 50 years, which is far longer than the planning period *T* in most cases. Therefore, the researcher assumes that one pipe can be replaced no more than one time during the planning period *T*.

***Failure cost over a planning period T***

Based on the assumption above, the failure cost during a planning period *T* is shown in Figure 4-2. The vertical dot line indicates the age boundary of the planning period *T*. A replacement activity is conducted at $\tau^*$, and $\tau_2$ means another replacement activity, which is outside the planning period *T*.

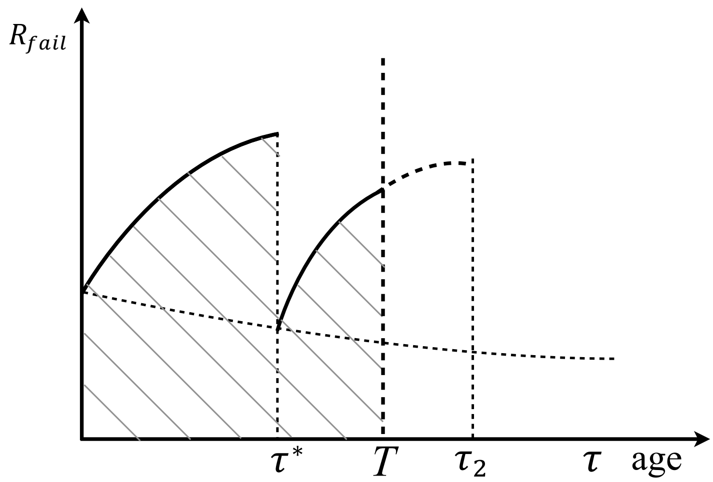



Figure 4-2 Repair cost rate during a planning period *T*

The total failure cost during a planning period *T* with one replacement at $\tau^*$ is given by:

$$C_{fail,\tau^*} = C_{fail} \cdot Nseg \cdot \left(\int_0^{\tau^*} f_{crp}(\tau)d\tau + \int_{\tau^*}^{T} f_{crp}(\tau - \tau^*)d\tau\right). \quad (4\text{-}4)$$

***Total cost during a planning period T***

The total cost of one pipe with a replacement at $\tau^*$ during a planning period *T*, is the summation of failure cost and replacement cost, shown as

$$C_{tot,\tau^*} = C_{repl} + C_{fail} \cdot Nseg \cdot \int_0^{\tau^*} f_{crp}(\tau)d\tau$$

$$+C_{fail} \cdot Nseg \cdot \int_{\tau^*}^{T} f_{crp}(\tau - \tau^*)d\tau, \quad (4\text{-}5)$$

where $C_{repl}$ is the replacement cost, which will be introduced in detail in Section 4.5. Equation (4-5) contains three parts:

(1) $C_{repl}$ is replacement cost, which may or may not happen during a given period *T*;

(2) $C_{fail} \cdot Nseg \cdot \int_0^{\tau^*} f_{crp}(\tau)d\tau$ illustrates the failure cost before the replacement activity at age $\tau^*$;

(3) $C_{fail} \cdot Nseg \cdot \int_{\tau^*}^{T} f_{crp}(\tau - \tau^*)d\tau$ indicates the failure cost after the replacement activity, where from the beginning of $\tau^*$, the reliability follows a decreasing trend with age increasing from the “as good as new” condition.

***Discretised cost formulas***

Practically, the repaired time is commonly recorded in date or in year. Therefore, the age of water pipes is a discrete variable. The corresponding formulas need to be discretised. The total cost during a planning year *T* is given as:

$$C_{repl} + C_{fail} \cdot Nseg \cdot \sum_{\tau=1}^{\tau^*} f_{crp}(\tau) + C_{fail} \cdot Nseg \cdot \sum_{1}^{T-\tau^*} f_{crp}(\tau - \tau^*), \quad (4\text{-}6)$$

where $\tau$ is a discretised age in year, $\tau = 1,2, \ldots T$.

***Cost function based on planning year t***

Replacement planning is usually based on a calendar year, rather than on age. Therefore, it is necessary to transfer the age specific total cost with $\tau$ to a calendar year specific total cost with *t* of planning year. Let $instD_i$ be the installed date of each pipe *i*, and $currD$ be the current date. The units of $currD$ and $instD_i$ are years.

The failure cost for replacing pipe *i* at its calendar year $t^*$ $(t^* = 1,2, \ldots, T)$ during the planning horizon *T* is given as:

$$C_{fail,i,t^*} = \sum_{t=1}^{t^*}\left[f_{crp,i}(t + currD - instD_i) \cdot C_{fail,i} \cdot Nseg_i\right]$$

$$+\sum_{t=1}^{T-t^*}\left[f_{crp,i}(t) \cdot C_{fail,i} \cdot Nseg_i\right], \quad (t = 1,2, \ldots, T) \quad (4\text{-}7)$$

where $Nseg_i$ indicates the number of segments of pipe *i*.

Based on the assumption that only one replacement activity can be enacted during the planning horizon *T*, the total replacement cost for replacing pipe *i* at its calendar year $t^*$ during the planning horizon *T*:

$$C_{repl,i,t^*} = C_{repl,i.} \tag{4-8}$$

Then the total cost for replacing pipe *i* at its calendar year $t^*$ during the planning horizon *T* is given by:

$$C_{i,t^*} = C_{repl,i,t^*} + C_{fail,i,t^*} \tag{4-9}$$

***Net present value of the total cost***

In practice, the economic objective in making a replacement decision is to minimize the net present value of the total system cost, which can be calculated by the summation of the total cost of each pipe *i*. Replacement investments usually span long periods of times. Therefore, the net present value of the asset should be calculated.

The net present value for total repair cost of replacing pipe *i* at its calendar year $t^*$, during the planning horizon *T* is given by:

$$PV_{fail,i,t^*} = \sum_{t=1}^{t^*} \left[\frac{f_{crp,i}(t+currD-instD_i)\cdot C_{fail,i}\cdot Nseg_i}{(1+r)^t}\right] + \sum_{t=1}^{T-t^*} \left[\frac{f_{crp,i}(t)\cdot C_{fail,i}\cdot Nseg_i}{(1+r)^{t+t^*}}\right] \tag{4-10}$$

The net present value for total replacement cost of replacing pipe *i* at its calendar year $t^*$, during the planning horizon *T*:

$$PV_{repl,i,t^*} = \frac{C_{repl,i}}{(1+r)^{t^*}} \tag{4-11}$$

The net present value for total cost of replacing pipe *i* at its calendar year *t*, during the planning horizon *T*:

$$PV_{i,t} = PV_{repl,i,t} + PV_{fail,i,t} \tag{4-12}$$

Total system cost indicates the total net present value of replacement planning cost (replacement cost and failure cost) of all the pipes in a water pipeline network. Total system cost is given as

$$C^{tot} = \sum_{\forall t, t=1,\dots,T} \sum_{i=1}^{n} PV_{i,t}^{tot}, \tag{4-13}$$

which indicates the net present values of the total system cost, where each pipe $i$ will be replaced in calendar year $t$, where $i = 1, \dots, n$, and $t = 1, \dots, T$.

## 4.4 REPLACEMENT GROUP SCHEDULING

Practically, when a single water pipe is selected to be replaced based on some decision making methods, the planners usually combine some other pipes, which are located near the selected one, to group as one replacement activity, because it is an efficient way to reduce the replacement cost.

If replacement planning considers all the replacement activities into groups for the whole network during a long planning period, this overall activity is defined as replacement group scheduling.

The problem of replacement group scheduling addressed in this research is generally expressed as follows, 'Given a water pipeline network with *N* individual pipes and an inventory of their information (length, diameter, material, soil type, zone area, geographic information system (GIS) information, and maintenance history information), as well as given a replacement planning period of *T* years, how should the pipes or pipe segments be scheduled into groups of replacement activities to maximise economic utility and minimise service interruption?'.

Replacement activities are usually scheduled in groups manually based on expert experience case-by-case in order to improve work efficiency, so as to reduce costs. This practice fails to provide an optimal solution, because replacement optimisation of water pipelines considering group scheduling needs to consider multiple criteria, where the optimised replacement solutions can hardly be determined only by expert experience. This section introduced the description of the three proposed group-scheduling criteria in this research, and the methodology for modelling the multiple criteria.

### 4.4.1 Criteria of the replacement group scheduling

Pipeline replacement activities can be grouped based on multiple criteria. However, three most critical criteria are (1) replaced pipes should be located in adjacent geographic areas; (2) they should share the same unique replacement methods or machinery, or (3) they cause interruption of services for the same customers. These three group-scheduling criteria are introduced as follows:

**Criterion 1: Shortest geographic distance**

Normally, water pipes are distributed in a large geographical area from more than one thousand $km^2$ (a small town) to more than one million $km^2$ (a state), constructed in different years. As a result, replacement activities are located in a vast geographical area and widely distributed. The cost of transportation is hardly ignorable. More widely distributed pipes cause higher cost in transportation of replacement teams and machinery. The notion of the criterion of the shortest geographic distance is that, if two pipes are adjacent to each other geographically, they will be grouped as one replacement activity to avoid unnecessary transportation cost, so as to reduce replacement cost.

**Criterion 2: Maximum replacement equipment utilization**

Replacing water pipes requires various pieces unique equipment and machinery, especially for the pipes with larger diameters (greater than 610mm). For instance, open-trench technology is usually employed in replacing a MSCL pipe with diameter of more than one metre. Heavy load machines such as backhoe, large crane, bulldozer, heavy load trucks, and trench boxes need to be utilised due to the large diameter and the heavy weight of pipes. Labours with special skills are also necessary for using these special machines. The costs of both the machines and the skilled labourers account for a considerable proportion of replacement cost. As a result, grouping pipeline replacement activities on account of sharing the same unique replacement machinery can enhance the machinery utilization. Maximizing the utilization of machines and skilled labours can reduce machinery utilization cost, so as to reduce replacement cost.

**Criterion 3: Minimum service interruption**

Replacing water pipelines in most areas requires shutting down the water supply and causing service interruption for customers. The water supply continuity is a key criterion for assessing service quality and reputation, and therefore reducing the service interruption is crucial for water utilities. If the two replacement activities cause an overlap area with service interruption, they might be conducted jointly, so that the total service interruption can be reduced.

### 4.4.2 Judgment matrix

Based on the three group scheduling criteria, the following judgment matrix $\mathbf{J}$ is defined to model the group scheduling:

$$\mathbf{J} = \begin{bmatrix} \varepsilon_{11} & \cdots & \varepsilon_{1j} & \cdots & \varepsilon_{1n} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ \varepsilon_{i1} & \cdots & \varepsilon_{ij} & \cdots & \varepsilon_{in} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ \varepsilon_{i1} & \cdots & \varepsilon_{nj} & \cdots & \varepsilon_{nn} \end{bmatrix}, \qquad i,j = 1 \cdots n$$

where $\varepsilon_{ij} \in [0,1]$, and

$$\varepsilon_{ij} = \min\left(\varepsilon_{ij}^{GD}, \varepsilon_{ij}^{EU}, \varepsilon_{ij}^{CI}\right) \tag{4-14}$$

where $i,j = 1,2,\dots,n$, and *i, j*, are the indexes of pipes, *n* is the total number of pipes in the network. $\varepsilon_{ij}^{GD}, \varepsilon_{ij}^{EU}$, and $\varepsilon_{ij}^{CI}$ are the group-scheduling factors of the three group scheduling criteria, which indicate the shortest geographic distance, the maximum replacement equipment utilization and the minimum service interruption, respectively.

### 4.4.3 The calculation of geographical distance

The geographical information of water pipeline networks contains the geographical coordinates for each pipe, which is captured by GIS.

As water pipes are linear assets, they are represented by series of continuous geographical coordinates. A massive continuous data can exaggerate the computing complexity. In order to simplify the computation, the coordinates of the centre point of each pipe substitute the massive continuous data.

To determine which pipes are close to a target pipe *i*, and how close they are, two indicators $\gamma_{ij}$ and $\gamma^*$ are introduced, where $\gamma_{ij}$ is the geographic distance (km) from pipe *i* to pipe *j*, and $\gamma^*$ is a user-defined maximum geographic distance (km).

If $\gamma_{ij} \le \gamma^*$, then pipe *j* belongs to the set of $G_i$, where $G_i$ means the replacement activity group for pipe *i*. Reflecting in the judgment matrix $\mathbf{J}$, $\varepsilon_{ij}^{GD}$ is equal to:

$$\varepsilon_{ij}^{GD} = \begin{cases} \frac{\gamma_{ij}}{\gamma^*}, & \gamma_{ij} < \gamma^* \\ 1, & \gamma_{ij} \ge \gamma^* \end{cases}, \tag{4-15}$$

### 4.4.4 Determination of equipment utilization

Replacement is defined as installing a new pipe to replace the existing pipe by either open-cut or trenchless technology. The answer to the question of "which types of machinery and skilled labours are suitable for particular pipes?" relies on the expert knowledge from water utilities and replacement contractors.

If the replacement activities of pipe $i$ and $j$ can employ the same machinery and skilled labourers, the replacement activities of pipe $i$ and $j$ will be grouped together.

In this research, it is assumed that the machinery utilisation is based on a pipe's diameters and materials; the relationship is given in Table 4-1

Table 4-1 Machinery utilisation based on materials and diameters

| Material | Diameter |
|---|---|
| Concrete, cement | <=125mm |
| | >125mm |
| Metal | <=220mm |
| | >220mm |
| Plastic | <=220mm |
| | >220mm |

It means that replacement of pipes in the same material and diameter group can use the same machinery. Therefore, pipe $i$ and pipe $j$ in the same hazard group, $\varepsilon_{ij}^{EU} = 0$, otherwise, $\varepsilon_{ij}^{EU} = 1$.

This assumption may be alternated by specific rules of machinery utilisation based on expert knowledge.

### 4.4.5 Service interruption for group scheduling criteria

Hydraulic calculation can be applied to estimate the customers, who are interrupted by replacing each pipe $i$. A well-known hydraulic software EPANET2[122] can be used to estimate the customers interrupted by each replacement activity. This software requires a number of hydraulic design parameters of water networks such as the level of the tanks and reservoirs, the curves of pumps; structural design parameters of each pipe such as length, diameter, material, and the number of customers that are directly connected to each pipe.

The numbers of customers interrupted by replacing pipe $i$ and pipe $j$ are denoted by $N_{c,i}$ and $N_{c,j}$, and their overlap number is denoted by $N_{c,i,j}$.

Reflecting on the judgment matrix $\mathbf{J}$, $\varepsilon_{ij}^{CI}$ is equal to:

$$\varepsilon_{ij}^{CI} = \frac{N_{c,i}+N_{c,j}-N_{c,i,j}}{N_{c,i}+N_{c,j}} \tag{4-16}$$

However, for water utilities, especially those small ones, there is no hydraulic information utilised in their systems. The number of customers interrupted $N_{c,i}$ is calculated based on the information provided by utilities, while the overlapping numbers, $N_{c,i,j}$ cannot be calculated without hydraulic information. Therefore an assumption is made that if pipe $i$ and pipe $j$ share the same node (for example, valves), $N_{c,i,j} = \min(N_{c,i}, N_{c,j})$, otherwise $N_{c,i,j} = 0$.

## 4.5 GROUP SCHEDULING BASED REPLACEMENT COST FUNCTION

The cost of pipe replacement is subject to its length, diameter and location, as well as the replacement technologies, machinery, skilled labours, and transportation. A replacement cost function associated with two components, fixed component and variable component, was developed by Kleiner [75], where fixed component is mobilization cost, and the variable component is the length-related cost. To fit for group scheduling, an enhanced replacement cost function is developed in this research, which contains three components, (1) length-related cost of pipe *i,* $C_{l,i}$, which depends on a pipe's length, diameter and material; (2) machinery and labour cost $C_{M,i}$, and (3) transportation cost $C_{d,i}$. The replacement cost function is given by:

$$C_{repl,i} = C_{l,i} + C_{M,i} + C_{d,i} \, . \tag{4-17}$$

Each item in Equation (4-19) is given by:

$$C_{l,i} = CL_i \cdot l_i \, , \tag{4-18}$$

$$C_{M,i} = CM_i + CSL_i \, , \tag{4-19}$$

and

$$C_{d,i} = Cv_i \cdot dis_i \, , \tag{4-20}$$

where $CL_i$ represents length cost rate (*$* per metre), which is usually given by water utilities; $l_i$ is the length of the pipe $i$; $CM_i$ and $CSL_i$ are the unit cost of machinery and skilled labour for replacing pipe $i$, respectively; $Cv_i$ is a unit cost for transportation, usually defined as *dollars per km*; and $dis_i$ is the transportation distance for replacing pipe *i,* which can be calculated using the same method of Section 4.4.3.

Defined $g = 1, \ldots, n$, where $g$ is an index of each group, and $x_{ig}$ is a judgment value, which

$$x_{ig} = \begin{cases} 1, & if \text{ pipe } i \text{ is in group } g \\ 0, & otherwise \end{cases}, \tag{4-21}$$

Considering the Judgment matrix (Equation (4-14)) described in Section 4.4, a relationship between $x_{ig}$ and $\varepsilon_{ij}$ is given as:

$$\begin{cases} x_{ig} = 1 \text{ or } x_{jg} = 1 \iff \varepsilon_{ij} \in (0,1) \\ x_{ig} = 0 \text{ or } x_{jg} = 0 \iff \varepsilon_{ij} = 1 \end{cases}.$$

For each group $g$, $\varepsilon_{ij} \in (0,1)$ can be interpreted to $x_{ig} = 1$ or $x_{jg} = 1$, which means that the pipes *i* and *j* are combined in one group; $\varepsilon_{ij} = 1$ can be interpreted to $x_{ig} = 0 \; or \; x_{jg} = 0$, where pipes *i* and *j* cannot be combined in one group.

Two assumptions were made for formulating group scheduling, similar to those made by Kleiner[75]:

Only one machine and labour team will be levied if a number of pipes fall into one group of replacement activities.

Then, the machinery and labour cost for pipes in group *g* is given by:

$$\overline{C}_{M,g} = \frac{\sum_{i=1}^{n}[(CM_i + CSL_i) \cdot x_{ig}]}{\sum_{i=1}^{n} x_{ig}}, \; (\sum_{i=1}^{n} x_{ig} \neq 0) \tag{4-22}$$

where $\sum_{i=1}^{n} x_{ig}$ represents the number of pipes in group *g*;

If a number of pipes fall into the same group of replacement activities, the transportation cost of this one group is given by:

$$\overline{C}_{d,g} = \frac{\sum_{i=1}^{n}(Cv_i \cdot dis_i \cdot x_{ig})}{\sum_{i=1}^{n} x_{ig}}, \; (\sum_{i=1}^{n} x_{ig} \neq 0) \tag{4-23}$$

Therefore, based on these two assumptions, the replacement cost function for pipe *i* can be transferred to:

If $\sum_{i=1}^{n} x_{ig} = 0$

$$C_{repl,i} = C_{l,i} + C_{M,i} + C_{d,i} \, . C_{repl,i}$$

If $\sum_{i=1}^{n} x_{ig} \neq 0$

$$CL_i \cdot l_i + \frac{\sum_{i=1}^{n}[(CM_i+CSL_i)\cdot x_{ig}]}{(\sum_{i=1}^{n} x_{ig})^2} + \frac{\sum_{i=1}^{n}(Cv_i \cdot dis_i \cdot x_{ig})}{(\sum_{i=1}^{n} x_{ig})^2}. \qquad (4\text{-}24)$$

Therefore, Equation (4-24) and Equation (4-13) is used for calculating the total system cost considering group scheduling.

## 4.6 IMPACT OF SERVICE INTERRUPTION

It is necessary to shut down water supplies temporarily in particular areas for water pipeline replacement. Generally the shutdown of water supply will lead to service interruption for customers. The impacts of service interruption can be categorized into three different aspects, (1) the type of interrupted customers, (2) the number of interrupted customers, and (3) the duration of the interruption.

All customers are divided into four categories based on the feature and impacts of water supply discontinuation, which are residential, industrial, commercial, and agricultural. To deal with the difference of impacts of each category, an impact factor $f_{C,i}$ is defined by water utilities; the details will be introduced in the case study of Section 6.4.1. To simplify the calculation, it is assumed that the customers affected by one pipe can only be included in one type of impact factor.

The number of interrupted customers of the replacement for each pipe *i*, $N_{C,i}$, has been introduced in Section 4.4.5. $N_{C,i}$ is a key factor, because it is not only related to alternative water arrangement cost, but also ruins social reputation, where the social reputation has significant impact and takes a long time to rebuild.

The duration of the interruption $Dr_{c,i}$ for replacing pipe *i* is introduced to calculate the impacts of service interruption. Zhang's [121] research showed that accumulated cost per customer per hour of water discontinuation can be dramatically increased by the duration of water discontinuation after six hours. Optimized replacement schedule needs to consider reducing the total duration of replacement activities or keeping all replacement activities within a specific acceptable duration. In this research, $Dr_{c,i}$ is a length related variable, which is affected by other factors such as material and diameter. $Dr_{c,i}$ is given as:

$$Dr_{c,i} = Dr^* \cdot l_i, \tag{4-25}$$

where $Dr^*$ indicates the duration of replacing one pipe segment, which can be defined by users, and $l_i$ is the length of pipe *i*.

The impact of service interruption for each failure of pipe $i$, $Ic_{rep,i}$ is given as:

$$Ic_{rep,i} = f_{c,i} \cdot N_{c,i} \cdot Dr^*, \tag{4-26}$$

and the impact of service interruption for each replaced pipe $i$, $Ic_{repl,i}$ is given as:

$$Ic_{repl,i} = f_{c,i} \cdot N_{c,i} \cdot Dr_{c,i}, \tag{4-27}$$

where $f_{c,i}$ is a user-defined value based on the significance of each pipe, and $N_{c,i}$ is the number of customers interrupted for each replacement pipe *i*, and $Dr_{c,i}$ is the duration of the service interruption.

Considering group scheduling, Equation (4-27) is modified as:

$$Ic_{repl,i} = \frac{\sum_{j=1}^{n}[f_{c,i} \cdot (N_{c,j} - N_{c,ij,g}) \cdot x_{jg}]}{\sum_{j=1}^{n} x_{ig}} \cdot Dr_{c,i} \tag{4-28}$$

where $i$ and $g = 1,2,,\dots,n$ . $N_{c,ij,g}$ is the interactive number caused by replacement pipe *i* and pipe *j*, which can be calculated using the method introduced in Section 4.4.5.

The total impact of service interruption for each replaced pipe *i,* at each year $t^*$, $Ic_{i,t}$ is given as:

$$Ic_{i,t^*} = Ic_{repl,i} + \sum_{t=1}^{t^*}\left[f_{crp,i}(t + currD - instD_i) \cdot Ic_{rep,i}\right]$$

$$+\sum_{t=1}^{T-t^*}\left[f_{crp,i}(t) \cdot Ic_{rep,i}\right], \tag{4-29}$$

Therefore, the total system impact of service interruption for the whole network is given as:

$$Ic^{tot} = \sum_{\forall t, t=1,\dots,T} \sum_{i}^{n} Ic_i^{tot}, \tag{4-30}$$

which indicates the total equivalent service interruption duration for all replacement activities of the whole water pipeline network during the planning period.

## 4.7 OBJECTIVES AND CONSTRAINS FOR THE RDOM-GS

For the system point of view, the total system cost contains those costs associated with the scheduled pipe replacements and the costs to repair pipe breaks for both the existing pipes and the new pipes. The net present value of the cost of pipe replacement decreases as its implementation is delayed due to time discounting. Conversely, the failure frequency or the probability of failure increases if the replacement is delayed, due to the aging and deterioration of the pipe. Therefore, the total system cost forms a convex curve, whose minimum point is determined by the replacement year *t* for each pipe *i*.

Two circumstances can be found, in that, 1) if the pipe is replaced too early, there is an economic loss due to money being spent sooner than necessary, since the service life of the pipe has not expired; 2) however, if the replacement of the pipe is delayed too long, there is an economic loss when additional money is spent for emergency repairs.

The total system impact of service interruption has a similar convex trend considering replacement and repair. The probability of failure increases if the replacement is delayed, so as to increase the number of customers interrupted by repair, on the contrary, more frequency of replacement may lead to more duration of interruption due to replacement of the whole pipe rather than the pipe segment.

Therefore, two objectives (1) minimizing total system cost and (2) minimizing total system impact of service interruption are introduced. The two objective functions are given as:

$$\textit{Minimize} \quad f_1(x) = C^{tot} = \sum_{\forall t \in T} \sum_{i=1}^{N} C_{i,t}^{tot} \tag{4-31}$$

$$\textit{Minimize} \quad f_2(x) = Ic^{tot} = \sum_{\forall t \in T} \sum_{i=1}^{N} Ic_i^{tot} \tag{4-32}$$

subject to the following constraints:

1. $0 \le \sum_{\forall t \in T} \sum_{i=1}^{N} C_{i,t}^{tot} \le B_T$, where $B_T$ is the total budget in the planning horizon *T*;
2. $1 \le S \le S_{\max}$, and $G \le N / S$, therefore, $N / S_{\max} \le G \le N / S \le N$, where *N* is the number of pipes, *S* is the number of pipes in one group of replacement activities, $S_{\max}$ is the maximum number of pipes in one group of replacement activities, and *G* is the total number of groups of replacement activities.

The decision variables are $i$ and $n$, where $i$ is the index of pipe in each group $g$, and $t$ is the replacement year $t = 1,2, \ldots, T$, in which $T$ represents the planning period.

## 4.8 STRUCTURE OF THE RDOM-GS FOR WATER PIPELINES

Figure 4-3 illustrates the structure of the RDOM-GS. The input information includes a) general information of the whole network such as material, length, and diameter of each pipe; b) GIS information such as the location coordinates of pipe and nodes; c) hydraulic information (if possible) such as design pressure and flow of each pipe and node; d) maintenance history information such as age, repair date, duration of repair and repair cost; e) some expert knowledge such as maintenance standards, machinery, skilled labour and technique. RDOM-GS contains three components, which are pre-analysis, group scheduling analysis, and multi-objective optimization analysis.

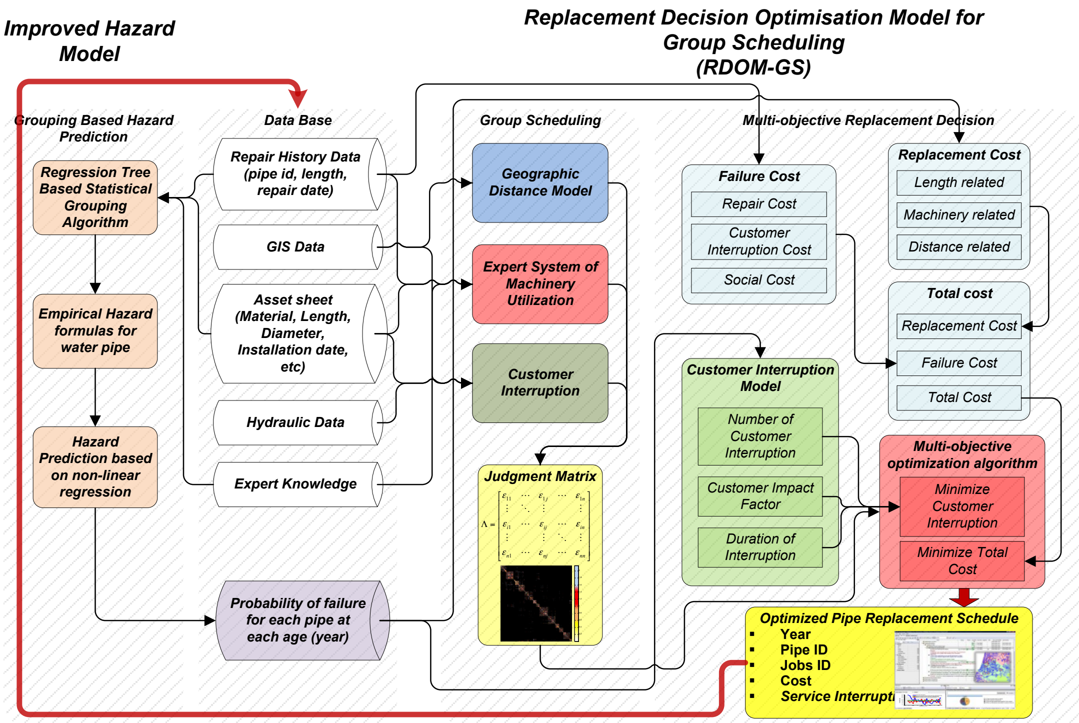



Figure 4-3 Structure of the RDOM-GS

The data used in the two proposed models, the improved hazard prediction model and the replacement decision optimization model for group scheduling, have to meet some requirements, therefore, data pre-analysis aims to filter the invalid data before any analysis for replacement decision making. The real data contains a number of data problems that may have a detrimental effect on the capability and accuracy of data analysis and decision-making. These data problems include (1) incomplete records that some data with blank information; (2) questionable or unexplained data, such as very short failure times and very short pipe length.

Then, all missing values are treated as invalid data in a data pre-analysis process, where these missing values should be excluded for the further analysis.

For the filtered data (valid data), the improved hazard prediction model was used to predict the hazard value for each pipe at each age. The output of the improved hazard prediction model is the hazard value for each pipe at each age.

Group scheduling analysis is implemented to seek the possible combinational solution for group scheduling, by taking three group-scheduling criteria into consideration. The aim is to reduce the combinational solution space of group scheduling through the judgment matrix. The details of group scheduling analysis have been described in Section 4.4, which contains the geographical distance model, machinery utilization model, and hydraulic model for service interruption.

The inputs of the group scheduling analysis contain two parts, (1) the asset sheet which contains the information of each pipe with asset ID, pipe length, pipe material, pipe diameter, geographic coordinate; (2) the expert knowledge inputs are also necessary such as rules for machinery used for different types of water pipe, the approximate number of customers affected, and the impact factor for different type of customer. The outputs for group scheduling analysis are the judgment matrix with three criteria, which is as a constraint of the solution space during the multi-objective optimization analysis.

The multi-objective replacement decision analysis aims to develop and balance the following two different objectives: 1) minimizing total life cycle cost (Equation (4-31)), and 2) minimizing service interruption impact (Equation (4-32)), in order to investigate the trade-off replacement solutions. Based on Equations (4-2), (4-7), and (4-21), this process starts with the calculation of failure cost and the group scheduling-based replacement cost. Then, the life cycle total cost of each pipe $i$ at selected year $t$ can be calculated by Equations (4-10) to (4-12). Based on the proposed service interruption model, through Equations (4-27) and (4-28), the impact of customer interruption for each replacement pipe $i$ at selected year $t$ can be calculated.

The inputs of the multi-objective replacement decision process contains four parts, (1) the asset sheet which contains the information of each pipe with asset id, pipe length, pipe material, pipe diameter, Soil type, installation date, geographic coordinate; (2) repair notification sheet for all repair history records, which contains the information of each recorded repair with asset id, pipe length, diameter, material, date of repair, date of installation; (3) repair cost records with asset id, pipe length, diameter, material, and repair cost; and (4) expert knowledge of the estimation of replacement cost. The outputs of the multi-objective replacement decision process are the values of the two objective functions for each possible group scheduling option.

Then a modified NSGA-II (developed in Chapter 5) as a multi-objective optimisation algorithm aims to investigate the trade-off solution between the two objectives of replacement group scheduling. The modified NSGA-II searches the possible group combinations iteratively with pipe ID, group ID, and replacement year, then calculates the two objective values and selects the winning combinations, just as the genes improved in evolution, cross over and mutate to find the optimised solutions.

The inputs are all the inputs in the multi-objective replacement decision analysis, and the pipe ID group ID and replacement year are coded in the optimisation algorithm. The outputs are the Pareto front for the two objectives with the total cost and the total service interruption impact. In the Pareto front, each point contains the information about which pipes should be due for replacement in each year, and which pipes can be scheduled as groups, with the information of replacement year, pipe id, group id, total cost and total service interruption impact during the planning period. This information will provide the guidance for operators to make replacement decisions.

## 4.9 SUMMARY

This chapter introduced a multi-objective replacement decision optimisation model for group scheduling (RDOM-GS) for water pipelines to give planners unambiguous information for optimizing their water pipeline replacement planning. Two objective functions were developed, based on cost functions and service interruption function. This model allowed planners to develop group replacement schedules against three criteria: shortest geographic distance, maximum replacement equipment utilization, and minimum service interruption, which were modelled by the Judgment matrix. The RDOM-GS integrated cost analysis, service interruption analysis, and optimization analysis, to deliver schedules that limit service interruptions and minimize total life-cycle cost.

Replacement group scheduling optimisation problem (GSOP) is considered as one of the multi-objective combinatorial optimisation, but it is different from any of the classic combinatorial optimisation problems. A modified evolutionary optimisation algorithm is developed and introduced in Chapter 5 to deal with the proposed multi-objective replacement decision optimisation for water pipelines.

# Chapter 5: An Improved Multi-objective Optimisation Algorithm for Group Scheduling

## 5.1 INTRODUCTION

Group scheduling for water pipeline replacement optimisation is complex, because it contains multiple criteria, multiple objectives, and its decision variables are in both time and space domains. However, the description of this problem can hardly be found in the literature. Therefore a mathematical modelling of the group scheduling optimisation problem (GSOP) and its computational complexity are discussed in Section 5.2. A modified NSGA-II to deal with GSOP is developed, and its procedure is introduced in Section 5.3, followed by the modified NSGA-II operators in Section 5.4. A comparison study for the modified NSGA-II and original NSGA-II based on two simplified objective functions is conducted in Section 5.5.

## 5.2 GROUP SCHEDULING OPTIMISATION PROBLEM (GSOP)

Optimisation problems can be divided into two categories: those with continuous variables and those with discrete variables, which are called the combinatorial problems [123]. Combinatorial optimization problems are characterized by their well-structured problem definition as well as by their huge number of solution spaces in practical application areas. Especially in areas like routing, task allocation, or scheduling, such kinds of problems often occur [124].

A multi-objective optimisation problem with $m$ objectives and $n$ parameters is usually described as a nonlinear programming problem, which is given as:

minimize: $f_m(X),\ X = (x_1, x_2, \dots, x_n), X \in S$

subject to: $g_i(X) = 0,\ i = 1,2,\dots,p$

$k_j(X) \geq 0,\ j = 1,2,\dots,q,$

where $f_m(X)$ indicates the $m$ objective functions, and $g_i(X)$ and $k_j(X)$ indicate the constrains.

The group scheduling optimisation problem (GSOP) can be considered as one of the multi-objective combinatorial optimisation, which is addressed as below:

Given a water pipelines network with $n$ individual pipes, with index of $i$, $i$ = 1,2,…,$n$, $NOP_g$ is defined as the number of pipes in each group $g$, where $g$ is the index of each group, $g$ = 1, 2,…, *NOG*. *NOG* is the total number of groups in the whole water pipelines network. Given a replacement planning horizon of $T$ years, and given a maximum number of pipes in each group $NOP^*$, $NOP^* = \max(NOP_g)$, the objective of GSOP is to find the best group index $g$, and the best year $t$, $t = 1,2,\ldots,T$, for each pipe $i$, in order to minimise the total system cost (Equation (4-31)), and to minimise the total system impact of service interruption(Equation (4-32)).

Two infinite situations are considered: (1) for all group $g$, $NOP_g$ equals to 1, which means that there is no pipe combined together, then *NOG* = $n$; (2) for all group $g$, $NOP_g = NOP^*$, which means that combined pipes in each group reach the maximum number $NOP^*$, then the *NOG* = $n/NOP^*$, where it has:

$$\frac{n}{NOP^*} \leq NOG \leq n.$$

Therefore, using the judgment value, $x_{ig}$, defined in Equation (4-21), $NOP_g$ is given as:

$$NOP_g = \sum_{i=1}^{n} x_{ig}. \qquad (5\text{-}1)$$

Based on that, there exists

$$\sum_{g=1}^{n} \sum_{i=1}^{n} x_{ig} = n, \qquad (5\text{-}2)$$

where the sum of all pipes in all groups is equal to the total number of pipes.

The possible numbers of the combinational solutions have an exponential relationship with the total number of pipes. There will be $NOG\hat{}N * T\hat{}N$ numbers of combinational options, if there are the number of *N* pipes and *NOG* number *of* replacement activity groups, and the planning period is *T* years, where "^" means the power operator. Normally, one water pipeline network contains at least thousands of pipes, and the replacement-planning period is usually more than 20 years, thus, searching from the corresponding huge solution space of the combinational options occupies huge computational memory.

A number of classical mathematical programming-based techniques such as the Newton method, linear programing, dynamic programming, nonlinear programming, had been developed to handle the combinatorial optimization problem [123]. However, GSOP is a complex combinatorial optimization problem involving multiple nonlinear objective functions, nonlinear constraints, and discrete variables. Therefore, in practice, heuristics such as evolutionary optimization technologies are commonly used even if they are unable to guarantee an optimal solution.

According to the literature review in Chapter 2, a number of contributions on evolutionary optimization algorithms had previously been developed. Since the multi-objective GSOP is hardly found at all in the literature, a well-known evolutionary optimization algorithm, Non-dominated sorting genetic algorithm-II (NSGA-II) is modified in order to solve the multi-objective GSOP. Several NSGA-II operators are redesigned or modified, and the details will be described in the following sections.

## 5.3 PROCEDURE OF THE MODIFIED NSGA-II

In this research, the modified NSGA-II contains a number of operators. Some of them are redesigned or modified for better performance. These include: a new designed coding method, an initialization method, a multi-point crossover operator, a modified non-dominated sorted mutation operator (considering keeping pipe in the same group replaced at the same year), non-dominated sort operator, a modified crowding distance operator, and a modified rank based selection operator.

The overall structure of the modified NSGA-II is illustrated in Figure 5-1. From the beginning, a set of initial population is generated based on the new coding and initialisation methods, indicated as $P_{gen}$, where *gen* means generation, and equals "0" in this step. Then, the population $P_{gen}$ is sorted with respect to its Pareto rank. By new individuals competed with the parent population $P_{gen}$, temporary population $Q_{gen}$ is achieved with the selection, crossover, and mutation operator. By combining the $P_{gen}$ and $Q_{gen}$, $R_{gen}$ is created. Then $R_{gen}$ is sorted by non-dominated sorting to produce a series of non-dominated set $F_t = \{F_1, F_2, \ldots, F_m\}$. Due to $F_1$ including the best individuals of $R_{gen}$, $F_1$ is added into the new parent population $P_{gen+1}$. If the size of $F_1$ less than *Pop* (number of individuals), then continue to add $F_2$ to $P_{gen+1}$, until add $F_3$. If the size of the population is beyond *Pop*, the individuals in $F_3$ are based on the crowding distance operation to reduce population size to *Pop*. Then repeat the circle again, until the number of generation is equal to the maximum generation. The outputs are a Pareto-set of solutions with the individuals with the information of group number *g* and the replacement year *t*, followed by the values of the two objective functions.

The procedure is shown in Figure 5-1. In the next section, the details of each operator will be introduced.

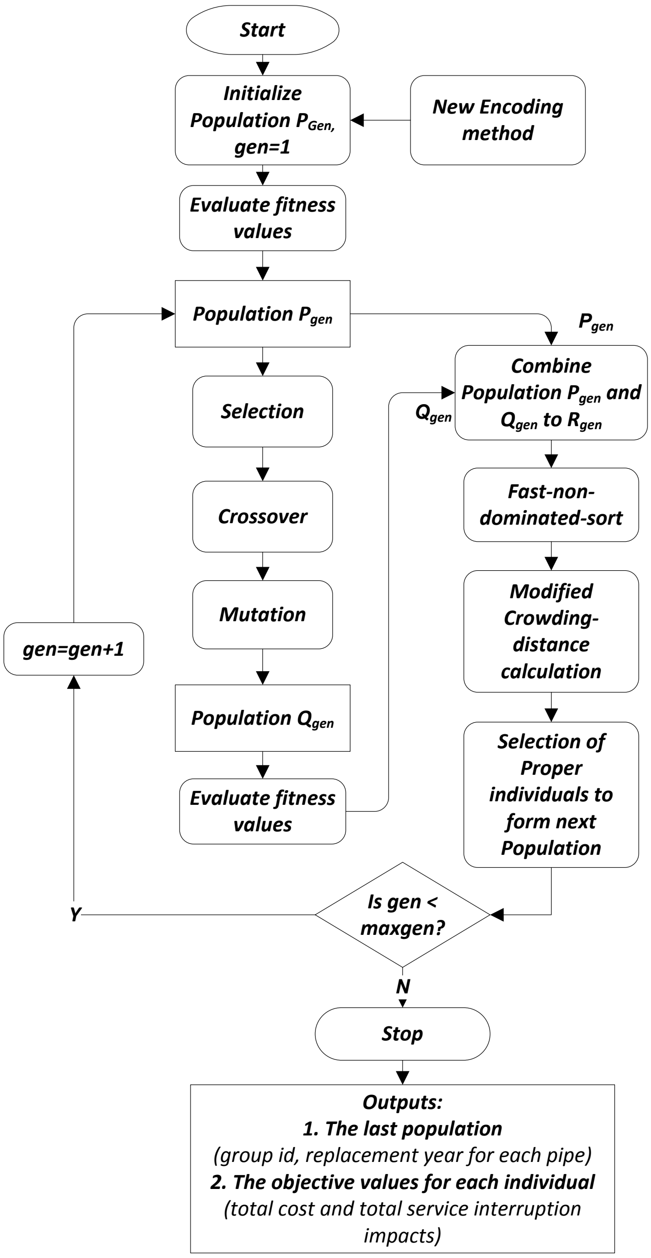



Figure 5-1 Procedure of the modified NSGA-II

## 5.4 OPERATORS OF THE MODIFIED NSGA-II

### 5.4.1 Encoding method

Encoding of the chromosomes in the NSGA-II depends on the objective functions of the practical problem. Since a replacement scheduling optimisation problem is one of the combinational problems, the two layers permutation encoding method is applied. It adopts an $n$-bit integer ($n$ genes) string with two layers to represent candidate solutions to the group scheduling, where the bit integers indicate the indexes' pipes in the orders from 1 to $n$. The first layer contains the value of the integer number $g$, $g = 1,2, \ldots, NOG$, which indicates the index of groups of replacement activities, and $NOG$ is the number of total groups of replacement activities. The second layer contains a value of $t$, where $t = 1,2, \ldots, T$, which represents the proposed replacement year $t$ for each pipe. Figure 5-2 shows the encoding method used for each replacement scheduling solution.

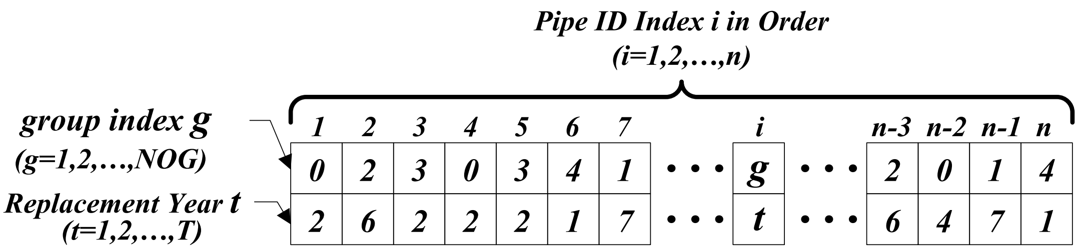
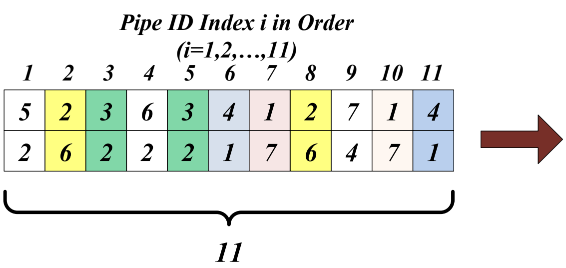



Figure 5-2 Encoding structure

For example, a solution for the replacement group scheduling of 11 pipes can be represented as the following bit string: [5,2,3,6,3,4,1,2,7,1,4/2,6,2,2,2,1,7,6,4,7,1]. Each bit indicates the group number or year number of each pipe *i*. "/" separates the group numbers' layer and the year numbers' layer, and "," separates each group number and each year number. The example string means that pipes 1, 7 and 10 are grouped in Group 1, pipes 2 and 8 are grouped in Group 2; pipe 3 and 5 are grouped in Group 3; pipes 6 and 11 are grouped in Group 4, and pipes 4 and 9 as independent replacement activities, which are not grouped with others, showed in Figure 5-3.




| *Job No.* | *Segments* | *Replacement* |
|---|---|---|
| *1* | *7, 10* | *7* |
| *2* | *2, 8* | *6* |
| *3* | *3, 5* | *2* |
| *4* | *6, 11* | *1* |
| *5* | *1* | *2* |
| *6* | *4* | *2* |
| *7* | *9* | *4* |

Figure 5-3 One example of encoding representation

In practice, there is a limitation of maximum number of pipes in each group, because planners cannot combine unlimited pipes into one replacement activity. Therefore, maximum number of pipes in one group $NOP^*$ is used, which means that

1,2,…,$NOP^*$ number of pipes can be combined together in one group, where $NOP^* < n$, and $NOP^*$ is a set value by planners or researchers.

### 5.4.2 Initialization operator

According to the permutation encoding method, the chromosomes should be the total combination of two layers $n \times T$ positive integers. In this research, the uniform distribution is applied to generalize the random integer number between the lower and upper bounds $\mathbf{x}^{(L)}$ and $\mathbf{x}^{(U)}$for each individual, where $\mathbf{x}^{(L)}$ and $\mathbf{x}^{(U)}$ are two vectors with length of $2 \times n$, $\mathbf{x}^{(L)} = [1, \dots, 1|1, \dots, 1]$, and $\mathbf{x}^{(U)} = [n, \dots, n|T, \dots T]$.

### 5.4.3 Crossover operator

The crossover operator corresponds to the multipoint crossover, where a number of pairs of chromosomes exchange their information on the right part of random chosen points. The probability of crossover between two chromosomes is denoted by $P_c$ and the number of crossover points is determined by a random integer $n_c$, where $n_c \in [1, n-1)$. Selecting two random chromosomes, and creating $n_c$ crossover points, the genes of one parent chromosome between the crossover points $2c-1$ and $2c$ are deleted, where $2c \in (2, nc)$. Then the deleted genes are added on to the location between the crossover points $2c-1$ and $2c$ of the other chromosome. The genes in the second layer will be recreated with the same crossover rule. For example, $A = [0,2,3,0,3 \uparrow 4,1,2,0,1,4/2,6,2,2,2 \uparrow 1,7,6,4,7,1]$ , $B = [0,2,3,0,2 \uparrow 4,1,0,3,1,4/4,3,5,2,3 \uparrow 1,7,4,5,7,1]$, where "↑" indicates the crossover points. Firstly 4,1,0,3,1,4 and 1,7,4,5,7,1 of $B$ are deleted, and then 4,1,2,0,1,4 and 1,7,6,4,7,1 to the corresponding deleted genes of $B$ are added, so the new individual is $B'' = [0,2,3,0,2 \uparrow 4,1,2,0,1,4/4,3,5,2,3 \uparrow 1,7,6,4,7,1]$. In a similar way, $A'' = [0,2,3,0,3 \uparrow 4,1,0,3,1,4/2,6,2,2,2 \uparrow 1,7,4,5,7,1]$.

### 5.4.4 Mutation operator

A mutation operator may be considered an important element in the design of the evaluation algorithms, for it helps to create diversity in the population. For a multi-objective group scheduling optimisation problem, a good mutation operator is essential for a good performance.

An adequate mutation rate is essential for a good performance of the NSGA-II, particularly in complex multi-objective combinatorial problems. High mutation rates lead to a random search throughout the search space, while low mutation rates present very small rates of progress towards the Pareto front, leading to time consuming and ineffective procedures.

In general, a fix value for the mutation probability may be adequate in the initial phase of the search but may become very ineffective, when the population is near the Pareto front. Moreover, another rule for mutation is that the worse the value of the objective function, the greater the mutation probability and vice versa [125]. Therefore, to improve the mutation operator for a group scheduling optimisation problem, the dynamic mutation operator based on the non-dominated fitness is introduced, where it has considered the influence of the mutation probability from the non-dominated fitness values.

The new established non-dominated fitness based Gaussian mutation operator is given as:

$$\mathbf{x}^{(t+1)} = \mathbf{x}^{(t)} + P_{m,\ j}{}^{(t)} \cdot \left(\mathbf{x}^{(U)} - \mathbf{x}^{(L)}\right) \cdot \boldsymbol{\delta}, \tag{5-3}$$

where $\mathbf{x}_{\boldsymbol{j}}{}^{(t)}$ indicates each individual *j, j=1,…Pop, Pop* indicates the population size, and $\mathbf{x}_{\boldsymbol{j}}{}^{(t)} = (x_{j,1}^{(t)}, \dots, x_{j,n}^{(t)})$ belongs to the *t*th generation. $\mathbf{x}^{(U)}$ and $\mathbf{x}^{(L)}$ are the upper and lower bounds vectors for each $x_{j,k}^{(t)}, k = 1, \dots, n$. $\boldsymbol{\delta}$ is a vector of normally distributed random numbers, $N(1, \sigma_j)$, where the mean is 0, and the standard deviation is $\sigma_j$. $P_{m,\ j}{}^{(t)}$ is the mutation probability for individual $j$ at *t*th generation, which is given as:

$$P_{m,\ j}{}^{(t)} = \sigma_j \cdot \left(1 - \rho \cdot \frac{t}{\max t}\right) \cdot fitness_j\ , \tag{5-4}$$

where *t* represents current evolution generation, *max t* indicates the largest evolution generation, and $fitness_j$ represents the non-dominated fitness value for individual $j$. Parameter $\rho$ is in the scalar between 0 and 1, $\rho \in [0,1]$.

At the beginning generation, the individuals are at a far distance from the Pareto front, therefore, large probability can maintain the diversity of the population, and the greater probability can deal with the non-good individuals (whose non-dominated fitness values are higher than others). In the end generation, the whole population has been basically close to the front, mutation rate decreases, therefore, it prevents the population degenerating earlier.

For optimisation of group replacement schedules, pipes combined in one group *g* should be replaced at the same year *t*. However, this cannot be guaranteed by the permutation encoding of the second layer. For example, in Figure 5-3, for pipe 2 and pipe 8, they are both grouped in group 2, but, initially, $t_2$ and $t_8$ may not be equal, where $t_i$ indicates the replacement year for pipe *i*, and *i* = [1,*n*]. Therefore, a reformation step is introduced in the mutation operator to keep the year *t* correct for each pipe *i* in each group *g*.

The reformation step is defined to keep $t_i$ identical in each group *g*, which is given as:

$$t_g{}^* = \frac{\sum_{i=1}^{n} t_i \cdot x_{ig}}{\sum_{i=1}^{n} x_{ig}}, \tag{5-5}$$

where $t_g{}^*$ is the new replacement year *t* for each pipe in group $g$, and $x_{ig}$ is a judgment value introduced in Equation (4-21). The reformation step is shown as below:

**Reformation step of mutation**

| | |
|---|---|
| Set $i, j, k$ , $k = 1, \dots, Pop$, $i = 1, \dots, n$, $j, g = 1, \dots, NOG$ | *k* is the index of individuals, *i* is the index of gene(pipe), *j* is the index of group number $g$ |
| for each individual $k$, | |
| for each group number $g$ | |
| find all the index $i$, where $j = g$ | |
| for all the index $i$, find all $t_i$ | $t_i$ is the replacement year value of each gene *i* |
| Let $t_g{}^* = \frac{sum\ of\ all\ the\ t_i}{number\ of\ all\ the\ t_i}$ | |
| New $t_i = t_g{}^*$ | |

### 5.4.5 Crowding distance operator

Crowding distance for a member of a non-dominated set tries to approximate the perimeter of a cuboid formed using the nearest neighbors of the member, which can easily handle the Case 1 problem showed in Figure 5-4. However, a main problem of crowding distance has been illustrated in Figure 5-4 that, individual $i$ and $i$+1 are located very close to each other in the left figure (Case 2), but they are far from the other individuals.

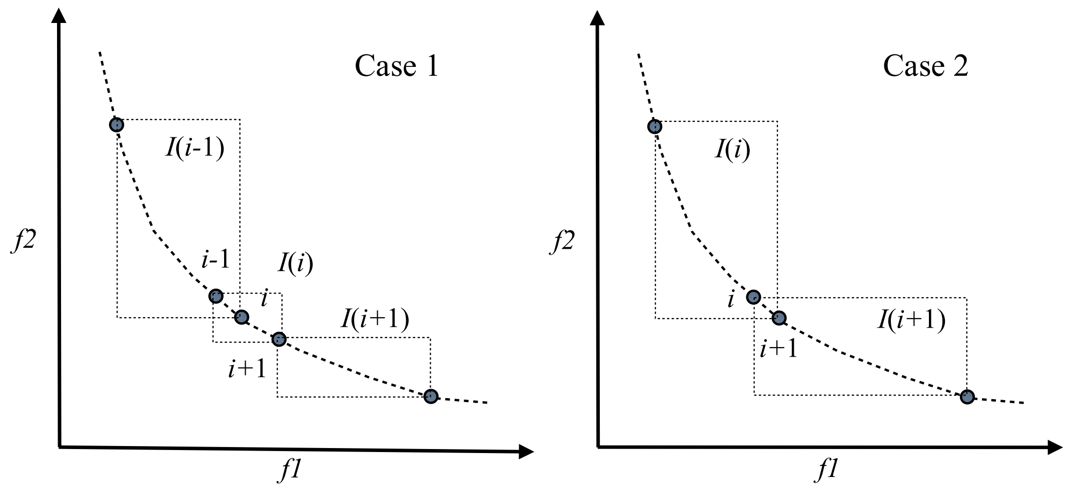



Figure 5-4 Illustration of the original crowding distance method

In Case 2, the values of individual $i$ and $i$+1 may be quite close, and both of them will be removed or reserved in crowding distance measurement. Obviously, it doesn't benefit the distribution of the non-dominated set. A better solution would be keeping one of the individuals, either individual $i$ or $i$+1 and removing the other individual. A minimum spanning tree [85] is used to deal with this problem. However, this method has a drawback in that it must calculate the minimum spinning tree every time, and it seems unclear for a solution if one node has two more edges connected. Based on these concerns, a simple modified crowding distance is proposed in this research to handle both situations in Case 1 and Case 2.

Based on the definition of crowding distance[83], the crowding distance for solution $i$ is given as:

$$I[i]_{distance} = I[i]_{distance} + \frac{(I[i+1].m - I[i-1].m)}{(f_m^{max} - f_m^{min})}. \tag{5-6}$$

and the modified crowding distance is given as:

$$I[i]_{distance} = I[i]_{distance} + \frac{(I[i+1].m - I[i-1].m)}{(f_m^{max} - f_m^{min})} \cdot \left\{1 + \frac{min[(I[i+1].m - I[i].m),(I[i].m - I[i-1].m)]}{max[(I[i+1].m - I[i].m),(I[i].m - I[i-1].m)]}\right\}, \tag{5-7}$$

where $\frac{I[i+1].m - I[i].m}{I[i].m - I[i-1].m}$ indicates the crowding deviation of $i$ between solution $i$-1 and $i$+1, which is shown in Figure 5-5.

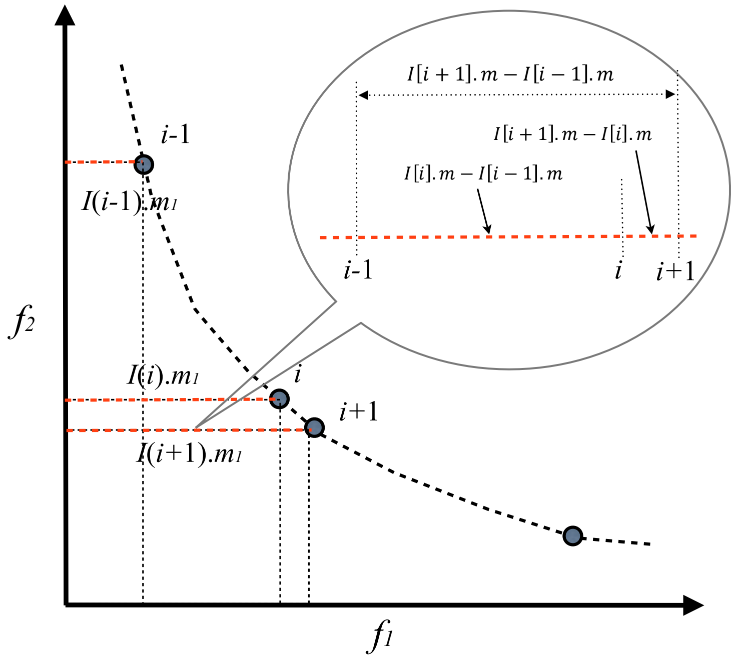



Figure 5-5 Modified crowding distance

Therefore, the procedure of the modified crowding distance is as below:

**Modified-crowding-distance-assignment (*I*)**

| | |
|---|---|
| $l = \|I\|$ | number of solutions in $I$ |
| for each $i$, set $I[i]_{distance} = 0$ | initialize distance |
| for each objective m | |
| $I = sort(I, m)$ | Sorting based on each objective value, |
| if $i$ = 1 or $i$ = $l$: | |
| $I[1]_{distance} = I[l]_{distance} = \infty$ | so that boundary points are always selected |
| | for all other points |
| otherwise: | |
| for $i$ = 2 to ($l$-1) | |

$$I[i]_{distance} = I[i]_{distance} + \frac{(I[i+1].m - I[i-1].m)}{(f_m^{max} - f_m^{min})} \cdot \frac{I[i+1].m - I[i].m}{I[i].m - I[i-1].m}$$

### 5.4.6 Selection Operator

The selection operator aims to ensure that better members of individuals in the current generation can be selected with higher probability of reproducing offspring in the hopes of acquiring higher fitness values in the next generation. At the same time, to ensure finding the global optimum, and to avoid converging to local optimum, the worse members of population have a smaller probability of being selected. Three often-used selection operators are tournament selection, roulette wheel selection and rank-based roulette wheel selection. The rank-based roulette wheel selection with its advantages of avoiding premature convergence and eliminating the need to scale fitness values is used in this research. The probability of an individual being selected is based on its fitness rank:

$$Rank(Pos) = 2 - SP + \left(2 \cdot (SP - 1) \cdot \frac{Pos-1}{n-1}\right), \tag{5-8}$$

where $SP$ is the selective pressure, $SP \in [1,2]$, $Pos$ indicates the position of an individual in the sorted population, where $Pos = 1, \dots, Pop$, $Pop$ is the population size.

## 5.5 COMPARATIVE STUDY

In order to test the proposed modified NSGA-II for GSOP, and to compare its performance with the original NSGA-II, the modified NSGA-II is used to solution a simplified GSOP. Commercial software Matlab R2012a is used to program the optimisation algorithms.

### 5.5.1 Simplified objective functions

Since the actual objective functions Equation(4-31) and Equation(4-32) are very complex, two simplified objective functions are designed for testing the performance of the modified NSGA-II for GSOP.

In Equation(4-7), the failure probability for each pipe *i* at each year *t* was assumed to be a constant value $f_{crp}$=0.001. Repair cost equals to \$500/unit, replacement cost assume to be \$500/meter.

Equation(4-28) is simplified as that $Ic_{repl,i}$ follows a normal distribution with mean equal to the diameter of pipe *i*, and the standard deviation assumed to be 1/4 of mean. It is reasonable that the larger diameter pipe has higher water flow, which supplies water to more customers.

One hundred pipes were randomly selected from a water pipe data set introduced in Section 3.3.2.

### 5.5.2 Parameter settings

NSGA-II and the modified NSGA-II are given integer-valued decision variables. The population size, *pop,* is 100, the maximum generation equals 100. One hundred pipes are considered ($n$ = 100), therefore, there are 100 design variables. Maximum number of pipes in each group is equal to 5, therefore the lower and upper bounds are $\mathbf{x}^{(L)} = [1, \dots, 1]$, and $\mathbf{x}^{(U)} = [100, \dots, 100]$. The number of objective function is 2.

A crossover probability of $p_C = 0.8$ and in the mutation operator, the standard deviation $\sigma_j = 2$, $\rho = 0.3$. In the selection operator, the selective pressure, $SP = 1.1$.

### 5.5.3 Results comparison

The multi-objective optimization has two goals to measure its performance, the convergence to the Pareto-optimal set and the maintenance of diversity in the solutions of the Pareto-optimal set.

Figure 5-6 shows the Pareto-fronts of the optimisation results for two optimisation methods. The blue solid square and the red dot indicate the Pareto-fronts calculated by NSGA-II and the modified NSGA-II respectively. During the same generation (gen = 100), the modified NSGA-II got better results, where its Pareto-front has a lower position compared with the NSGA-II one, which shows that the modified NSGA-II has better optimisation results in the same generation, for getting replacement schedules subject to lower total cost and lower service interruption.

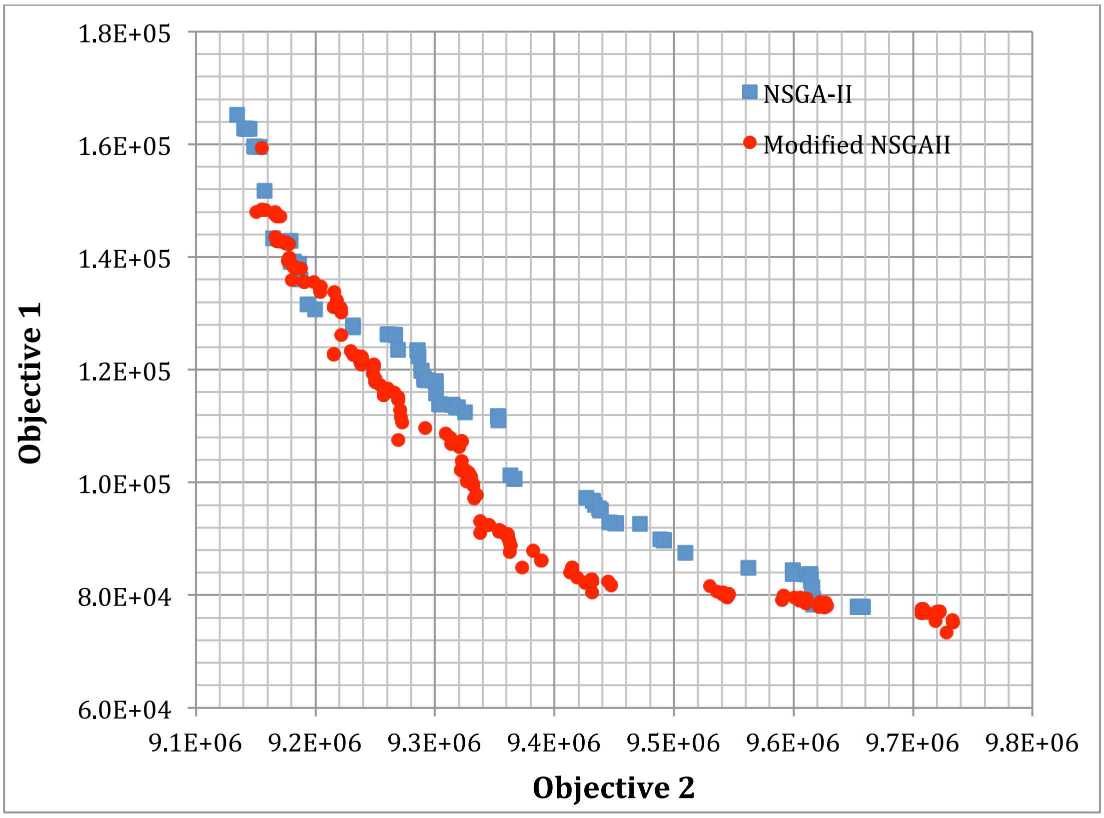



Figure 5-6 Pareto-fronts of the optimisation results for NSGA-II and the modified NSGA-II

To measure the diversity in the solutions of the Pareto-optimal set, $\boldsymbol{\Delta}$ metric was introduced [83], where a set of good solutions is necessary to be spanned over the entire Pareto-optimal region, and the $\Delta$ is to measure how the solutions are spanned, see equation below,

$$\Delta = \frac{d_f + d_l + \sum_{i=1}^{N-1} |d_i - \bar{d}|}{d_f + d_l + (N-1)\bar{d}}, \tag{5-9}$$

where $d_i$ is the Euclidean distance between consecutive solutions in the obtained non-dominated set of solutions, $\bar{d}$ is the average value of $d_i$, $d_f$ and $d_l$ are the Euclidean distances between the extreme solutions and the boundary solutions of the obtained non-dominated set, and *N* is the total number of the solutions.

$\Delta_1$ for NSGA-II equals to 1.16, and $\Delta_2$ for the modified NSGA-II equals to 1.07, where $\Delta_1 > \Delta_2$. The smaller the $\Delta$ is, the better the distribution of the solution is, therefore, the modified NSGA-II has made a better diversity in the solutions of the Pareto-optimal set than the NSGA-II.

## 5.6 SUMMARY

In this chapter, the candidate firstly described the group scheduling optimisation problem (GSOP) and its computational complexity, followed by the development of a modified NSGA-II to deal with the GSOP, which includes the introduction of the procedure and the operators for the modified NSGA-II. Finally, a comparison study was conducted based on the original NSGA-II and modified NSGA-II. The results showed that the modified NSGA-II has a better convergence to the Pareto-optimal set and results in better diversity in the solutions of the Pareto-optimal set.

A case study for a water utility is described in Chapter 6 to show the application of the improved hazard model (Chapter 3) and the RDOM-GS (Chapter 4 and Chapter 5).

# Chapter 6: A Case Study

## 6.1 INTRODUCTION

This chapter introduces a real case study from a water utility in Queensland to test and validate the proposed two models, (1) the improved hazard model for water pipes, and (2) the RDOM-GS. This water utility is one of the participants of the Cooperative Research Centre for Infrastructure and Engineering Asset Management (CIEAM), and provides water and wastewater services to more than 850,000 consumers. To support the study, the water utility provided a number of sets of data, including pipeline network data and work order data (in Excel spread sheets) and GIS data (in MapInfo files), described as follows:

Pipeline network data indicates the general information of the water pipes, which has 71,571 sets of raw data with the information of pipe ID (an unique identification for each pipe), pipe length (metres), pipe material types, pipe diameters (millimetres), construction date, and sub area ID (an identification for particular area defined by the water utility).

Work order data is the repair history data, which has 6,459 sets of raw data with information of pipe ID (a unique identification for each pipe), repair work order ID (an unique identification for each repair activity), repair start date, repair end date, activity description (to describe the activity in details), street name (where the pipe is located), and suburb name (where the pipe is located).

GIS data includes all the geographical information in MapInfo files for the water network, which includes geographic coordinates of water pipes, nodes, valves, pump stations and reservoirs.

The three files, the pipeline network data file, the work order data file, and GIS data files, can be linked by the pipe ID, so that all general information such as pipe length, diameter, material, location can be shared within the three files.

This case study includes a three-steps process: (1) data pre-analysis to investigate the provided data, to exclude invalid data, and to analyse the general characteristics; (2)

statistical-based hazard prediction analysis using the proposed improved hazard model, which has partitioned data into different subgroup based on their homogeneity, calculate empirical hazard for each subgroup, generate fitted hazard curve for failure prediction; (3) replacement decision optimisation for group scheduling using the proposed RDOM-GS, which gives an optimised replacement planning taking total cost and customer interruption into consideration, followed by a comparison analysis to show how well the replacement planning is working, compared with the method that does not consider the group scheduling.

## 6.2 DATA PRE-ANALYSIS

### 6.2.1 Overview of the water pipeline network

This water pipeline network services a community in Queensland, Australia, and comprises 66,405 pipes (total length of 3,640km, at an average length of pipe of 54.79m), with diameters from 20mm to 1440mm, in 11 different materials, installed between 1937 and 2012. It services a population of more than 850,000 inhabitants. Based on the pipeline network data file, an overview of the network was presented in Table 6-1.

Table 6-1 Overview of the water pipeline network

| Item | Description |
|---|---|
| Pipe's Diameter | 20mm, 32mm, 40mm, 45mm, 50mm, 63mm, 75mm, 80mm, 90mm, 100mm, 110mm, 150mm, 200mm, 220mm, 250mm, 300mm, 375mm, 411mm, 450mm, 500mm, 510mm, 525mm, 565mm, 590mm, 600mm, 660mm, 700mm, 750mm, 800mm, 850mm, 900mm, 915mm, 960mm, 965mm, 1050mm, 1125mm, 1290mm, 1440mm |
| Pipe's Material (*11* types) | Asbestos Cement(AC), Cast Iron Cement Lined(CICL), Concrete(CONC), Copper(CU), Fibre Reinforced Pipe(FRR), Galvanised Steel(GAL), Glass Reinforced Plastic(GRP), Glass Reinforced Plastic(HOBAS), Ductile Iron Cement Lined(DICL), Mild Steel Concrete Lined(MSCL), Unplasticised Poly Vinyl Chloride(UPVC) |
| Pipe's Length | From 0.1m to 1363.9m |
| Zone area types | RURAL (RUR), URBAN (URB), HIGH DENSITY URBAN (HDU), CBD |
| Population | More than 850,000 inhabitants |

### 6.2.2 Age Profile of the Water Pipeline Network

The oldest water pipes in the network date back to 1937. Around 102km of the total length of pipes now in operation were installed before 1960. The construction history and the cumulative length of pipe being installed for each calendar year are shown in

Figure 6-1 and Figure 6-2. The blue bars show the total pipe length installed at each calendar year in kilometres, with red number labels marked.

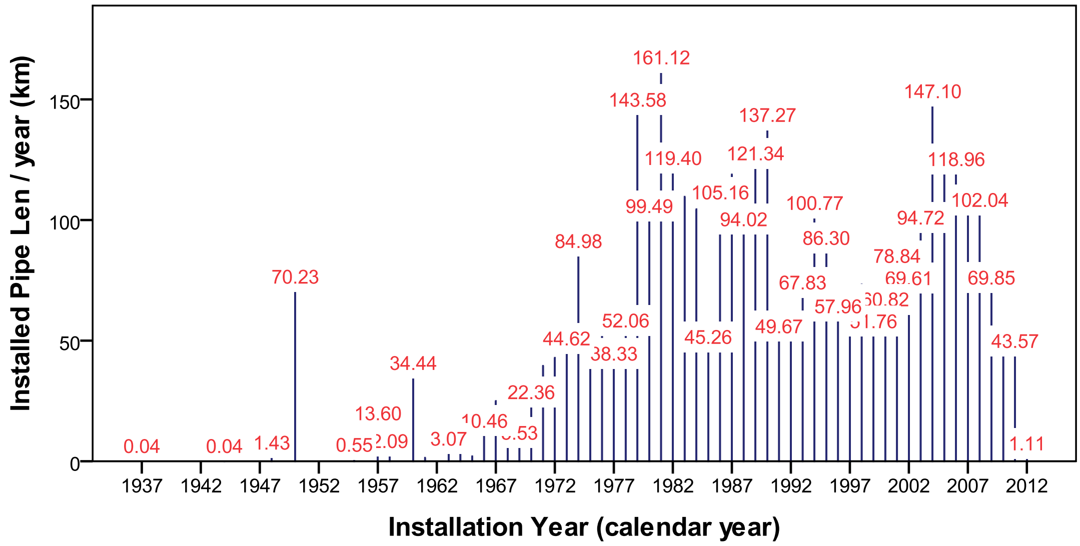



Figure 6-1 Length of pipe being installed for each calendar year

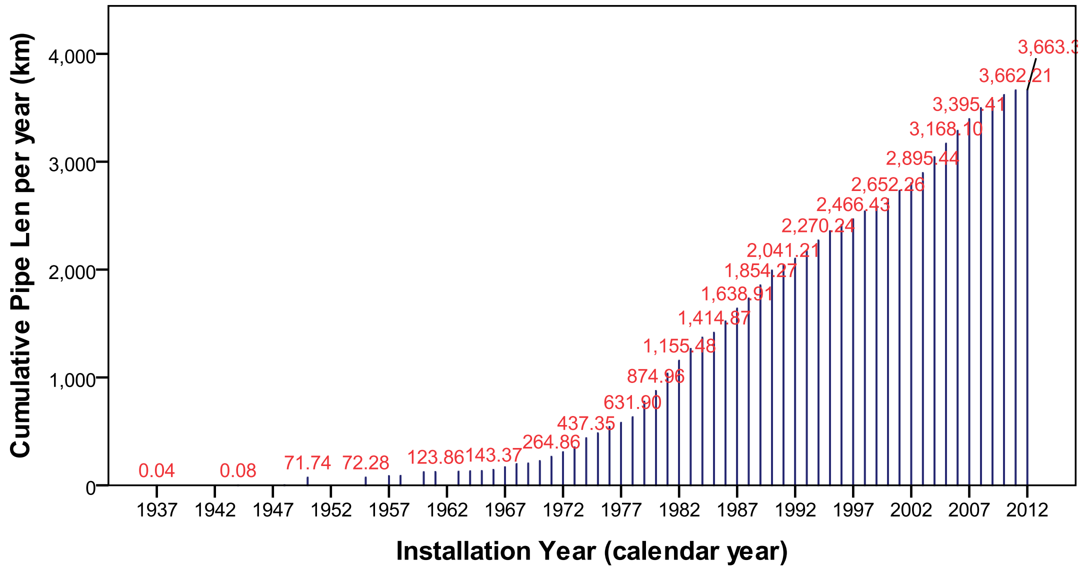



Figure 6-2 Cumulative length of pipe being installed for each calendar year

From Figure 6-1 and Figure 6-2, most water pipes were installed after 1970, and increasing trends of pipe installation happened until 1981 with a highest value of installed pipe in length (161.12km) in 2012. After that, the value decreases to 51.76km in 1998, followed by another increase till the recent year.

Throughout the water pipeline network, the most commonly used material of pipes are UPVC pipes and AC pipes of 1477km and 1385km in total length, followed by

DICL, MICL, and CICL. Other material includes CU, FRR, GAL, GRP, and pipes marked as NOINF, which means the pipes lacking material information. Figure 6-3 shows the total length of pipe with different material types.

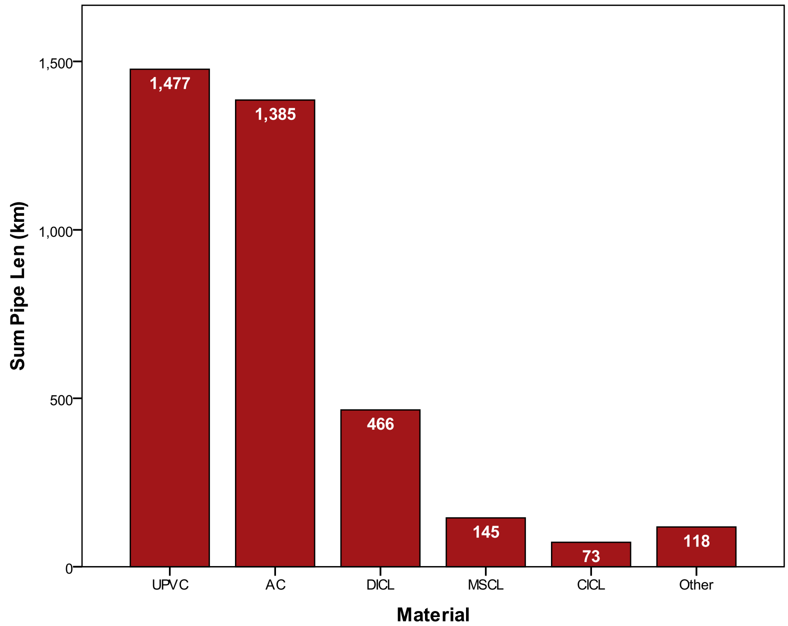



Figure 6-3 Total length of pipe by material type

Figure 6-4 compares the six material types for diameters, which shows that material type has a significant relationship with diameter. Most UPVC and AC pipes have small diameters around 150mm; DICL and CICL has larger range of diameters; MSCL pipe has largest average diameter of around 700mm, where, in general, most of the water mains with diameter larger than 500mm are MSCL pipes.

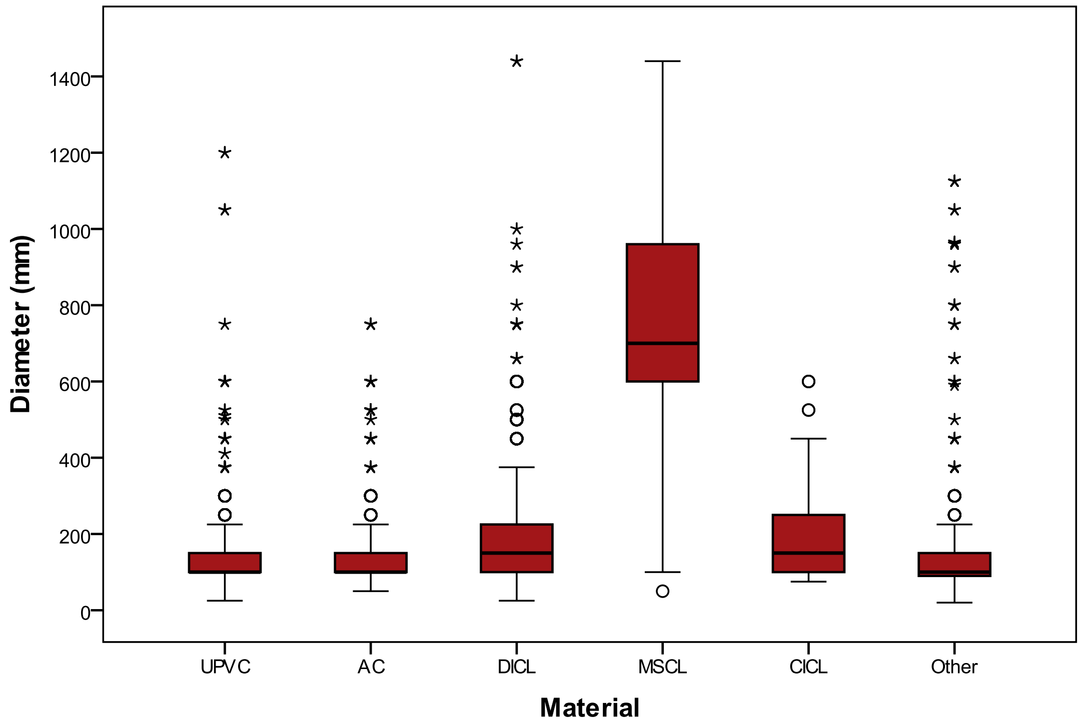



Figure 6-4 Box plot for different material types of diameter

Figure 6-5 compared six material types for the installation date. Almost all concrete or cement pipes were installed before 1960. During the years from 1961 to 1990, a significant increase of water pipe installations can be seen. Nearly half the numbers of the total pipes (3/5 of total length) were constructed in this period. The most commonly used materials in that period were ductile iron, grey cast iron and mild steel. In 1960, the first PVC pipes were installed and have become the preferred pipe material for replacements and expansions after 1970s. CICL pipes were constructed in the early years around 1950 and most of them were alternated by DICL in recent years.

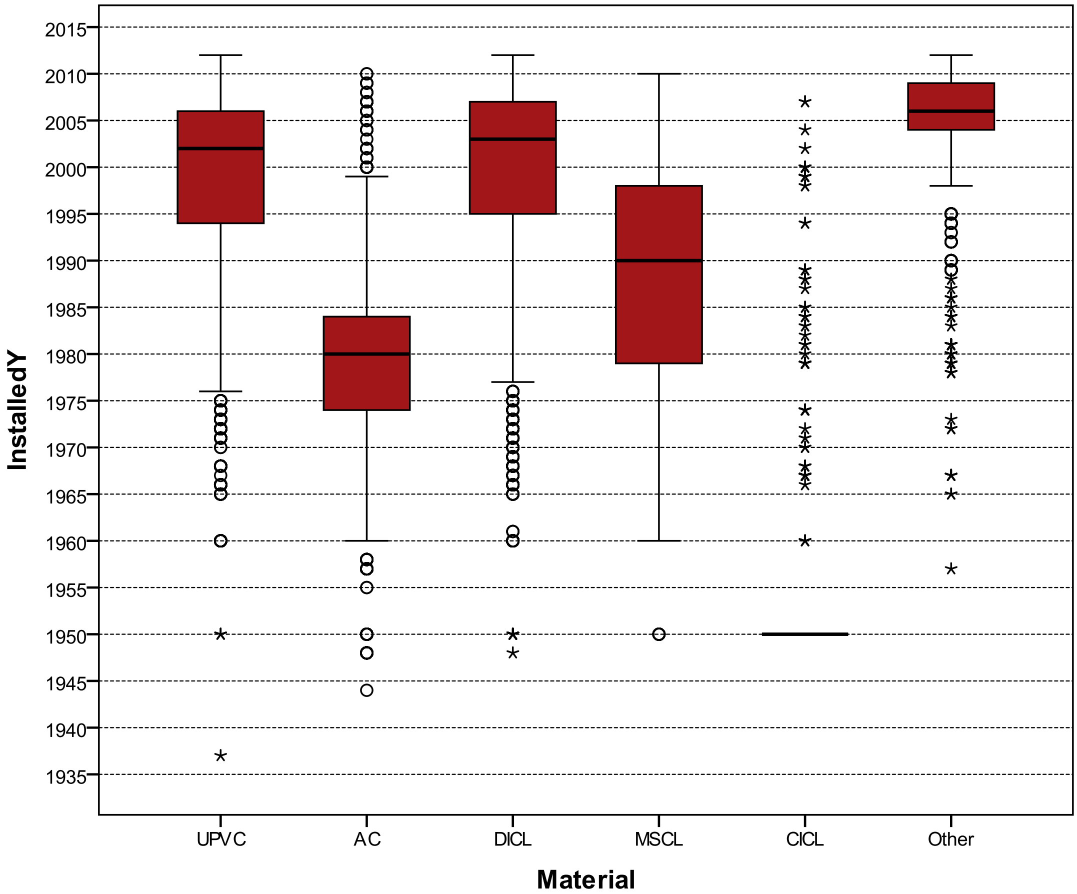



Figure 6-5 Box plot for different material types of installation date

### 6.2.3 Repair history of water pipe

The observation period over which the repair history records were collected and kept is just more than 10 complete years from 2002 to 2012. The water company conducted 6,459 repair jobs for unexpected breaks. Some of these data were found to be missing for various reasons, only 4,635 sets of valid records are with complete information of ID, length, material, diameter, installed date, repair date and repair cost, which includes 2,926 pipes, which indicates that a number of pipes were repaired two or more times. Over 10 years, the water utility spent around AUD$4 million to repair the water pipes. Figure 6-6 shows that the repair cost correlated with the number of breaks, where the repair cost rose from 2000 to 2010, and decreased slightly in 2005, and then peaked at AU$0.86 million in 2010.

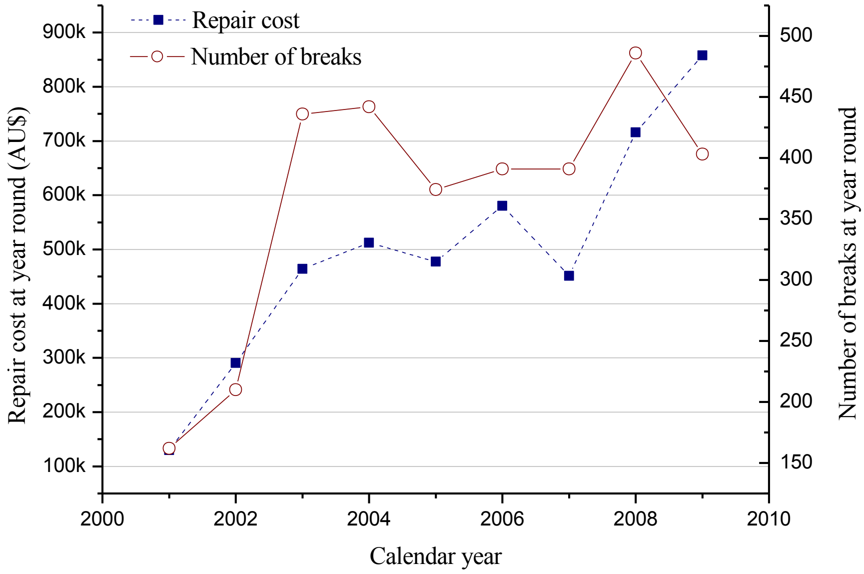



Figure 6-6 Repair history from 2000 to 2010

The repair records corresponded to six different pipe materials. Figure 6-7 showed the number of failures by material type, and that AC pipe has the highest number of failures (1,458), followed by UPVC (574). CICL, DICL and MSCL had 123, 80 and 23 failures respectively. Other pipe materials had a total of 16 failures during the 10-year observation period.

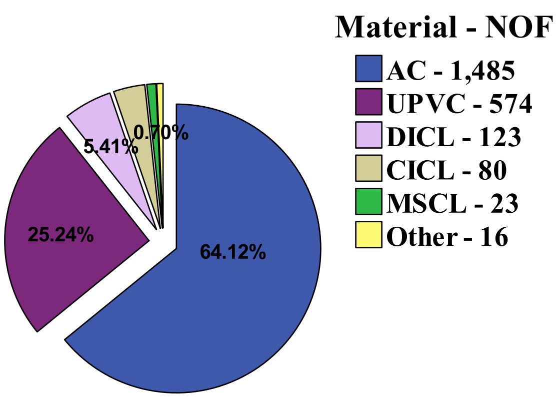



Figure 6-7 Number of breaks by material types

In practice, water pipe should be treated as a combination of a number of pipe segments. Repair activities are only for pipe segments rather than the whole water pipe, which is introduced in Chapter 4. Therefore, to illustrate the situation of water pipe failures in the network, the number of breaks pre 100km by material types are introduced and shown in Figure 6-8. Most failures happened in AC pipes at its early installed date. CICL has more failures pre 100km than DICL, which explains the reason of the substitution of DICL with CICL.

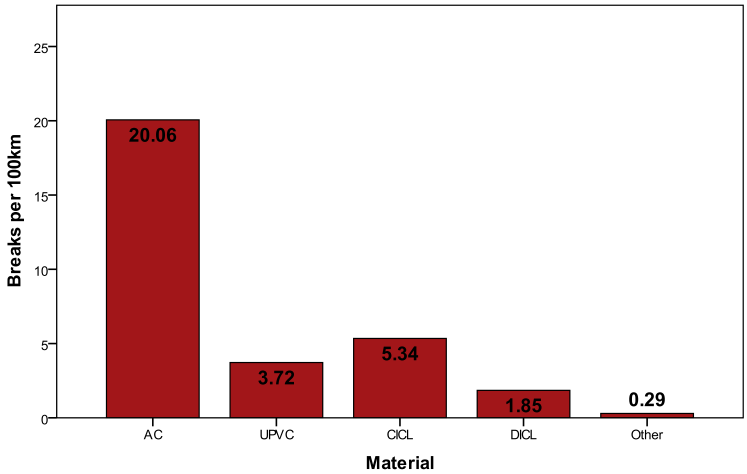



Figure 6-8 Number of breaks per 100km by material types

Table 6-2 is a summary of pipes based on types of material. It illustrates that the water network consists mainly of AC (29.6%), DICL (20.3%), and UPVC (42.0%) pipes. From the failure record point of view, AC and UPVC take 66.3% and 25.2% of the total failure records, which means 10% of AC pipes and 1.02% of UPVC pipes had failure records from 2000 to 2012.

Table 6-2 Summary of pipes based on types of material

| Material | No. of pipes | % of total pipes | No. of failures | % of total failures | No. of failures/ No. of pipes (%) |
|---|---|---|---|---|---|
| AC | 20,359 | 29.6 | 3,072 | 66.3 | 10.00 |
| CICL | 1,374 | 2.0 | 128 | 2.8 | 0.26 |
| DICL | 13,953 | 20.3 | 195 | 4.2 | 0.06 |
| MSCL | 1,269 | 1.8 | 47 | 1.1 | 0.04 |
| UPVC | 28,870 | 44.1 | 1,168 | 25.2 | 1.02 |
| Other* | 1,488 | 2.2 | 25 | 0.5 | 0.01 |
| Total | 67,313 | 100 | 4,635 | 100 | |

* Other includes: MS, HDPE, GRP, STEEL, MDPE, POLY and PP

### 6.2.4 Repair history of service interruption

There were a total of 6,687 sets of valid repair records for service interruption with the following structure with work order, asset ID, statues, number of properties affected. The asset ID can be linked with the information of pipe length, material, and diameter.

A total of 776 sets of repair were planned, compared with 3463 unplanned repairs and 2447 sets of repair records without this information. All repair activities affected totally 256,843 houses, 86 factories, and 2 shopping centres. Within this number, unplanned repair and repair without planned information caused service interruption to a majority of houses and factories with 221,451 houses and all 86 factories and 2 shopping centres, while planned repair caused only disruption to 35,392 houses.

## 6.3 HAZARD CALCULATION AND PREDICTION

### 6.3.1 Statistical grouping analysis

Based on the procedure proposed in Section 3.3, the hazard calculation starts at the statistical grouping analysis.

The data for statistical grouping are given in two files:

3. Work order sheet: work order sheet recorded the failure/repair date of each repair activity, and there are 2,926 valid sets of failure/repair records totally from 2002 to 2012;

4. Asset sheet: asset sheet recorded the general information of each pipe with pipe length in metres, pipe diameter in millimetres, pipe materials, and pipe installed date. That contains 71,282 sets of valid records.

***Application Results***

*Step 1 outputs*

Pipe's material type is a major factor or parameter in terms of statistical grouping. Figure 6-9 shows a significant positive linear correlation between the average failure rates and the average age for each material type, except AC and MSCL, which is considered an outlier. In Step 1, the number of failures/repairs per 100 metres is applied as the response variable for fitting the regression model. From Figure 6-9, most plastic pipes have lower average ages while CICL has the longest average life. AC and MSCL are considered as an outlier because it has shown a higher and lower value of failures/100m. Thus AC and MSCL will be treated as an independent group in the regression tree analysis in Step 2.

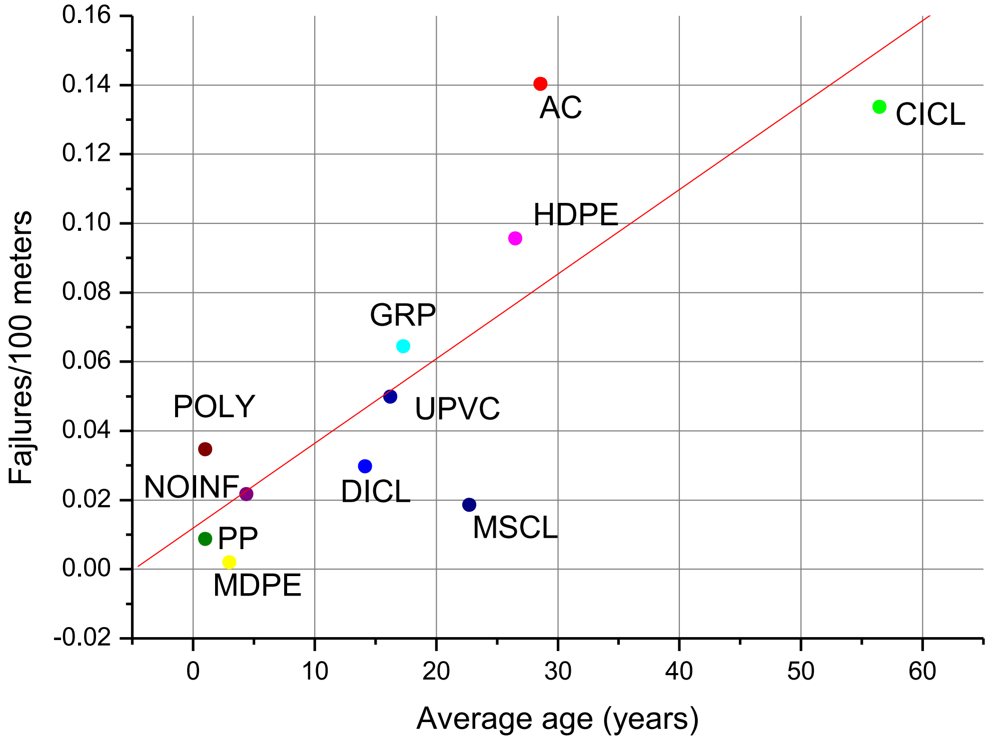



Figure 6-9 Relationship between failures/100m and average age for each material type

*Outputs from Step 2 and Step 4*

Table 3-1 shows the final results of statistical grouping based on Step 2 and Step 3, which contains 10 groups, with the listed statistical grouping criteria, number of pipes' ID, percentage of total length, number of failure records, and percentage of total number of failures. Group WG stands for Whole Group.

Table 6-3 Statistical grouping criteria, statistical grouping results and the information for each group

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| **Group Number** | **Length (m)** | **Material** | **Diameter (mm)** | **Numb er of pipes** | **Total length %** | **Numbe r of failure record s** | **Total number %** |
| Group 1 | Length> | AC | Diameter<=12 | 10549 | 19.41 | 1383 | 46.71% |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| | 1 | | 5 | | | | |
| Group 2 | Length> 1 | AC | Diameter>125 | 8106 | 18.38 | 532 | 17.97% |
| Group 3 | Length> 1 | MSCL | All range | 1216 | 3.96 | 27 | 0.91% |
| Group 4 | Length> 1 | CICL, DICL, GRP | Diameter <=105 | 4838 | 2.60 | 84 | 2.84% |
| Group 5 | Length> 1 | CICL, DICL, GRP | Diameter >10 5 | 9199 | 12.33 | 152 | 5.13% |
| Group 6 | Length> 1 | UPVC, NOINF | Diameter <=212.5 | 23516 | 34.19 | 613 | 20.70% |
| Group 7 | Length> 1 | UPVC, NOINF | Diameter>212 .5 | 3413 | 6.66 | 124 | 4.19% |
| All pipes | All range | All materials | All range | 71282 | 100.00 | 2960 | 100.00% |

### 6.3.2 Empirical hazards for each group

Table 6-4 showed the parameters of the fitted hazard curve for each group. The selected wear-out point, and the estimated parameters for each group, are also shown on each line. The wear-out point is the point from which the subgroup pipes are assumed to start aging. For the estimated parameters, 'lamda' gives the estimated exponential rate; 'Scale' and 'shape' indicate the scale parameter and shape parameter for the piecewise hazard, respectively.

Note that the determination of the wear-out point and the curve fitting results should only be considered as one of the many possible reasonable solutions to the grouping issue because of the complexity of real life data and the limitation of the optimisation procedure. Therefore, cautions are needed in interpretation and application wherever these results do not match engineering experience.

Table 6-4 Hazard model parameters for each group

| Group Number | Wear-out point | lamda (*10^-5) | Scale | Shape |
|---|---|---|---|---|
| Group 1 | 19 | 9.30 | 266.93 | 2.6601 |
| Group 2 | 35 | 5.80 | 1011.45 | 1.7456 |
| Group 3 | 25 | 4.45 | 5901.17 | 1.1946 |
| Group 4 | 25 | 7.81 | 6263.19 | 1.0529 |
| Group 5 | 52 | 3.91 | 208.79 | 2.2912 |
| Group 6 | 13 | 2.90 | 1514.10 | 1.4769 |
| Group 7 | 13 | 2.30 | 1806.59 | 1.2715 |

Figure 6-10 to Figure 6-16 shows the calculated hazard for each group, the empirical hazard (blue bar) with fitted piecewise hazard model curve (red line) for each group.

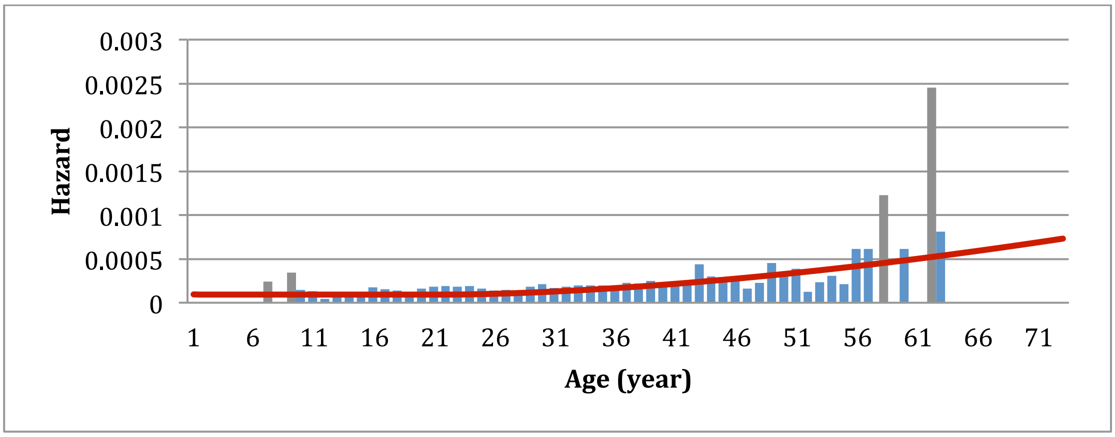



Figure 6-10 Hazard curve for group 1

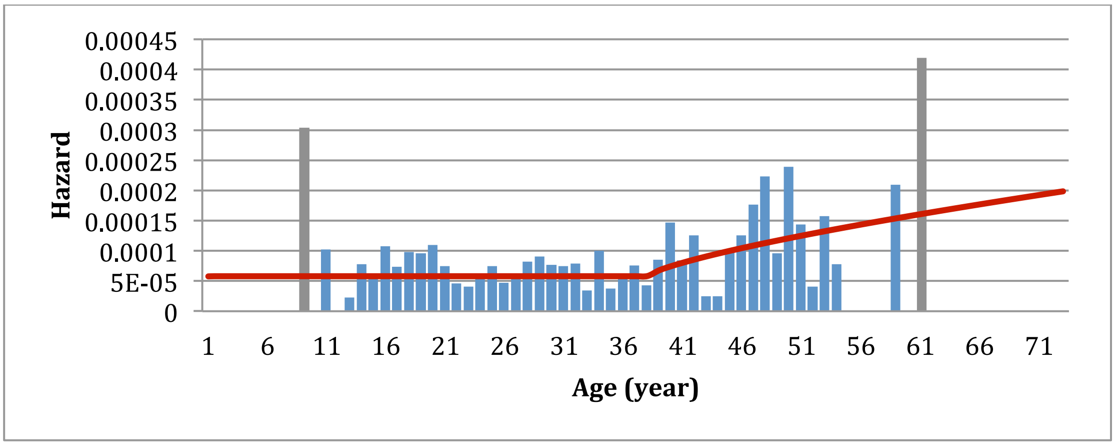



Figure 6-11Hazard curve for group 2

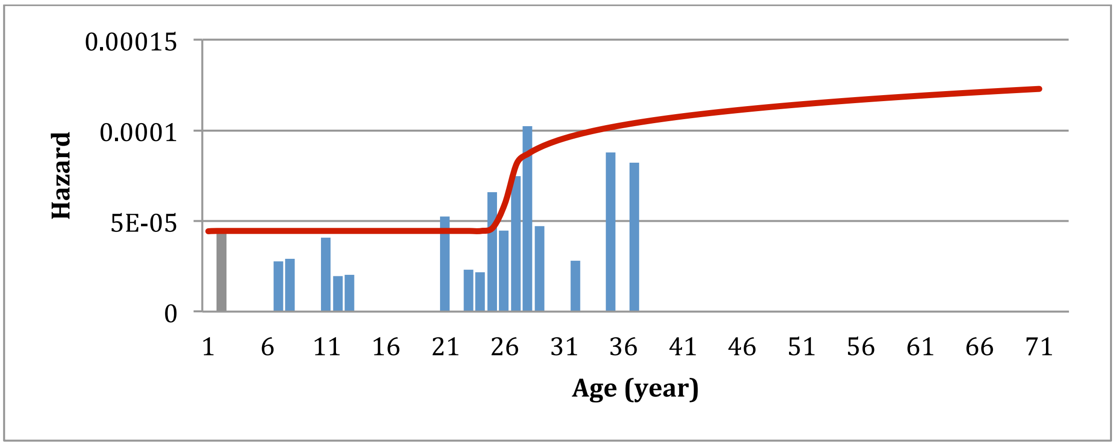



Figure 6-12 Hazard curve for group 3

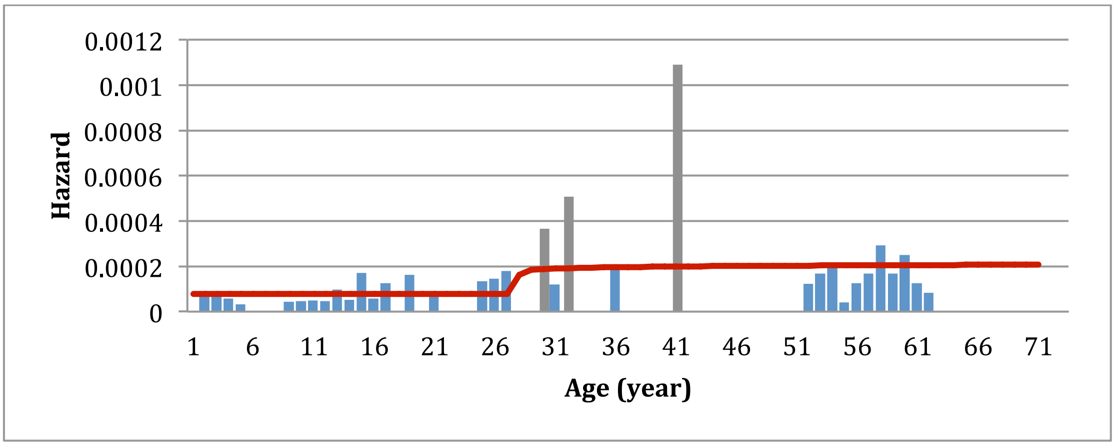



Figure 6-13 Hazard curve for group 4

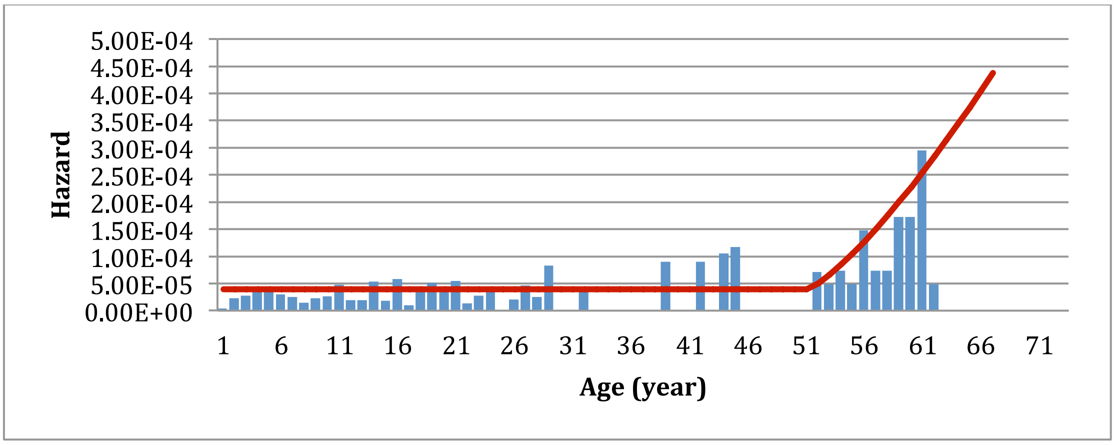



Figure 6-14 Hazard curve for group 5

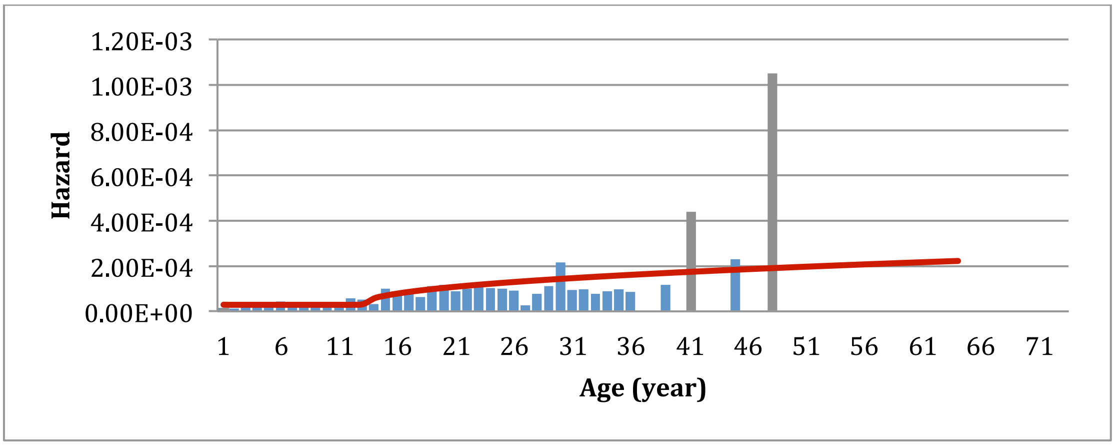



Figure 6-15 Hazard curve for group 6

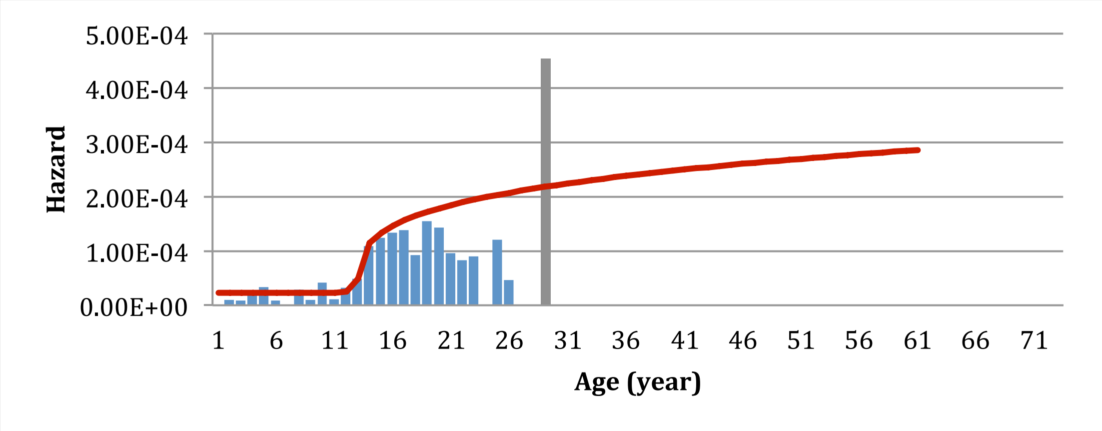



Figure 6-16 Hazard curve for group 7

Figure 6-17 showed the comparison of the fitted hazard curve for each group. It can be seen that hazard curves between groups are clearly distinctive from each other, with different distribution patterns. Hazard curves have different wear-out points between groups. Group 1 and Group 5 show dramatically increasing trends after wear-out points, while hazards in other groups are gradually increased in their wear-out periods.

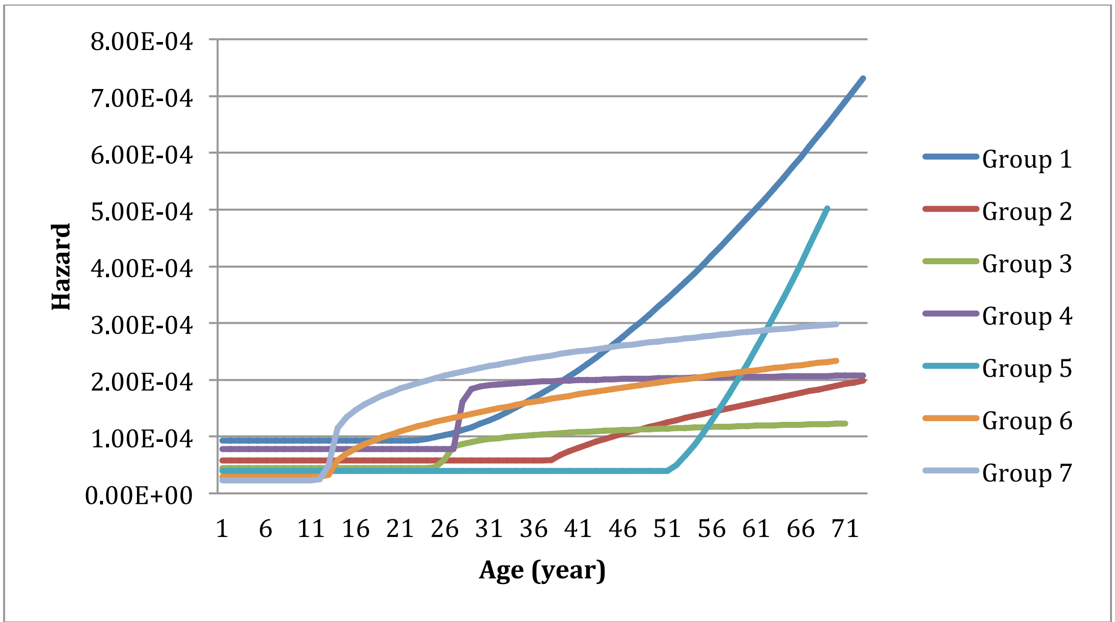



Figure 6-17 Comparison of the fitted hazard curve for each group

### 6.3.3 Predicted number of failures for each group

Figure 6-18 to Figure 6-24 showed the predicted number of failures for each group. For each graph, the blue bars indicate the empirical number of failures for each calendar year, the red solid lines show the number of failures for each group calculated based on the hazard calculated previously and the total pipe length in each calendar year, and the red dot lines indicates the predicted number of failures for each group. Since the failure records only have less than ten years failure observation, which started from 31/06/2002 and ended at 31/06/2012, the number of failures in 2002 and 2012 were only a half year's observation, therefore, lower values of the number of failures can be noted at the blue bars at 2002 and 2012.

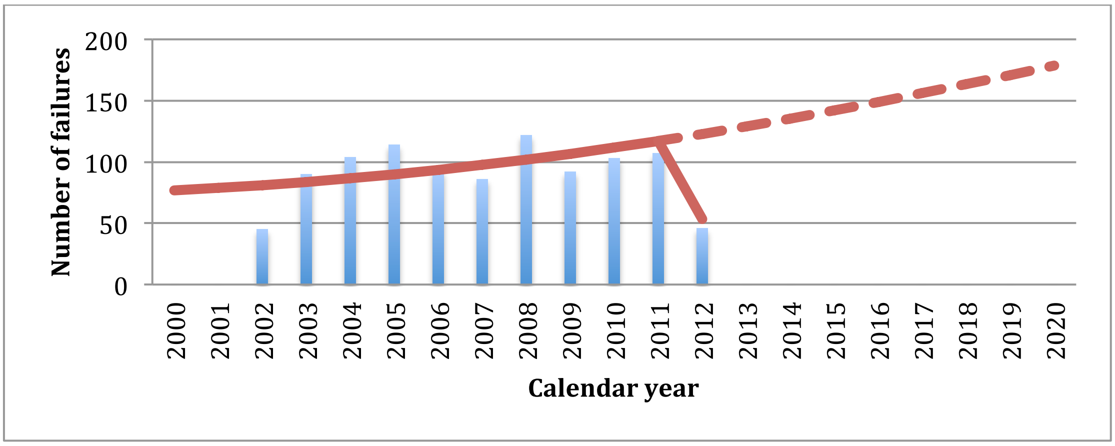



Figure 6-18 Predicted number of failures for group 1

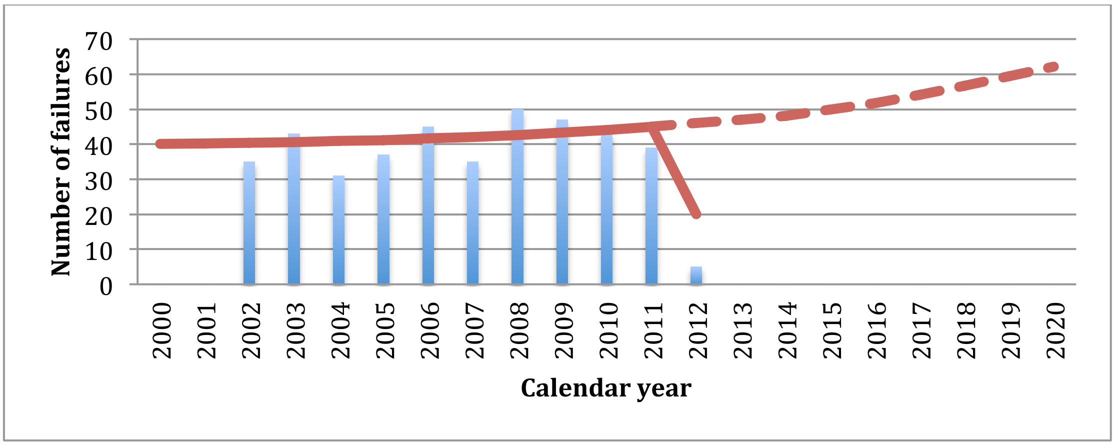



Figure 6-19 Predicted number of failures for group 2

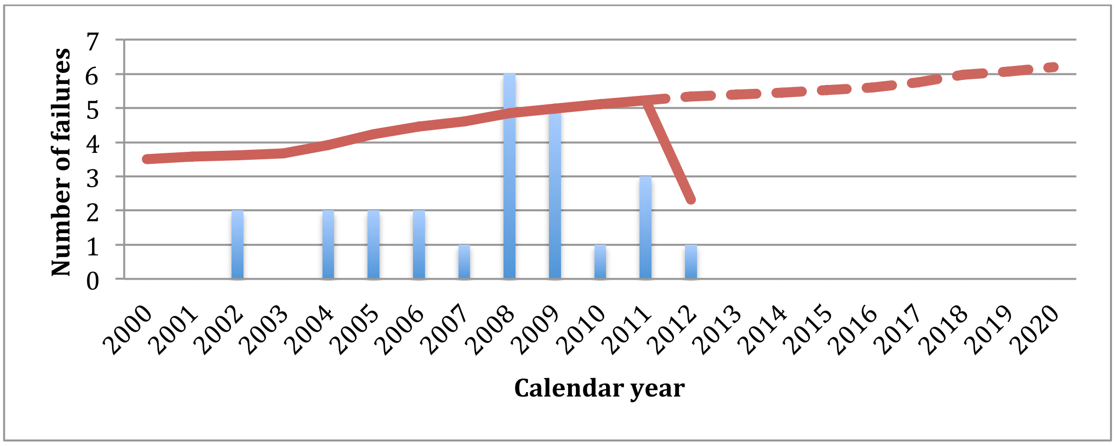



Figure 6-20 Predicted number of failures for group 3

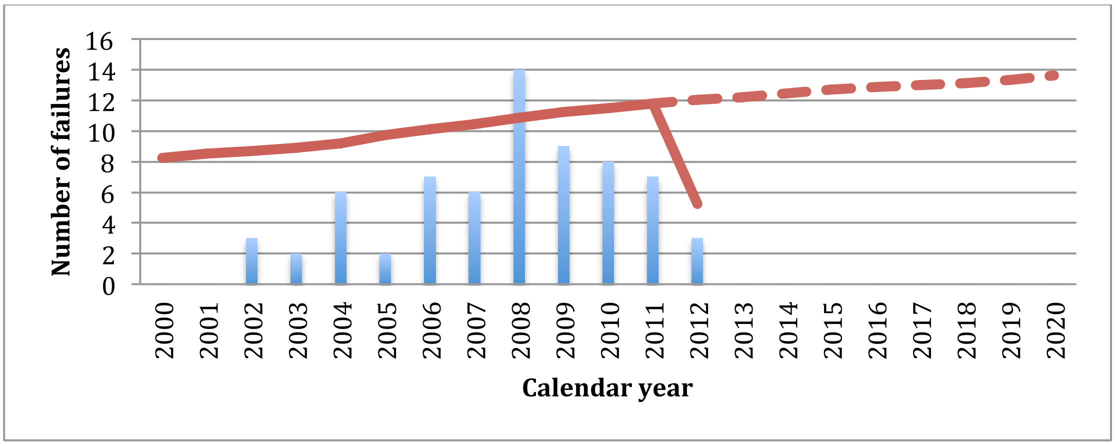



Figure 6-21 Predicted number of failures for group 4

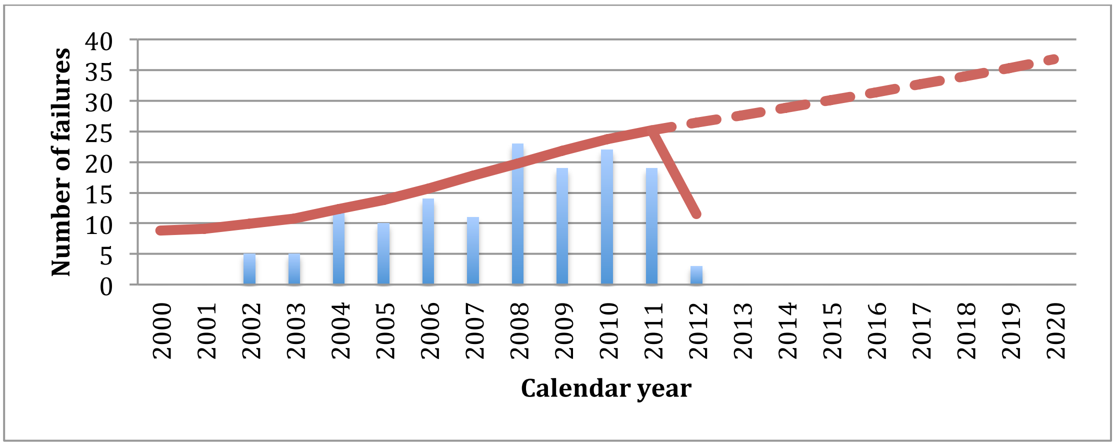



Figure 6-22 Predicted number of failures for group 5

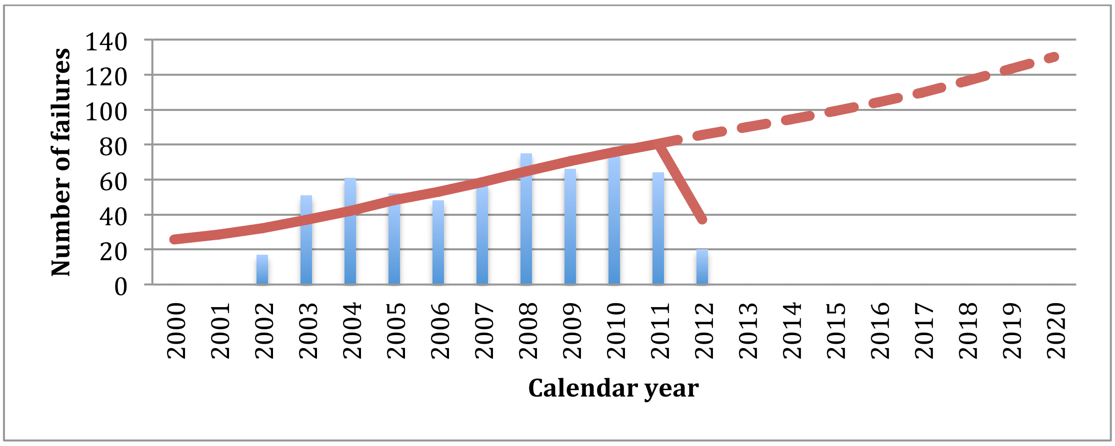



Figure 6-23 Predicted number of failures for group 6

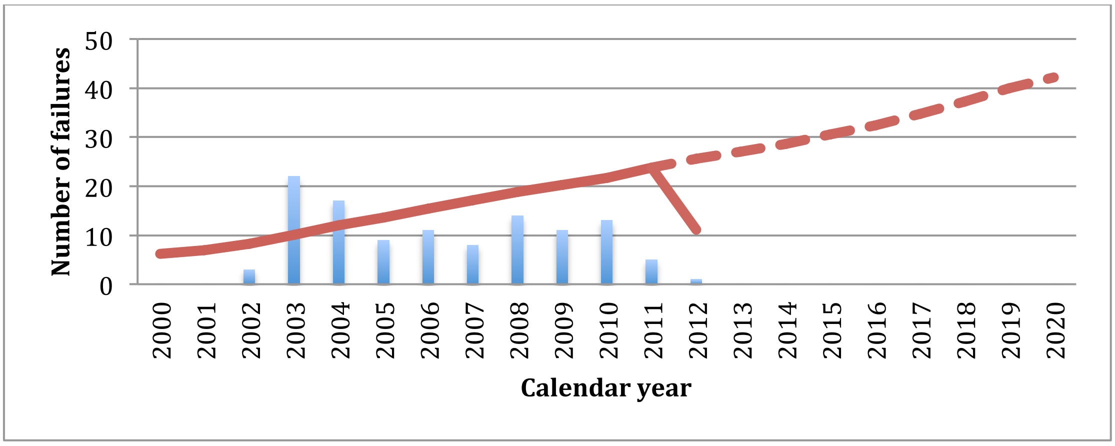



Figure 6-24 Predicted number of failures for group 7

Figure 6-25 showed the overall prediction results for all pipes in the network, which were calculated based on the value summation of all groups.

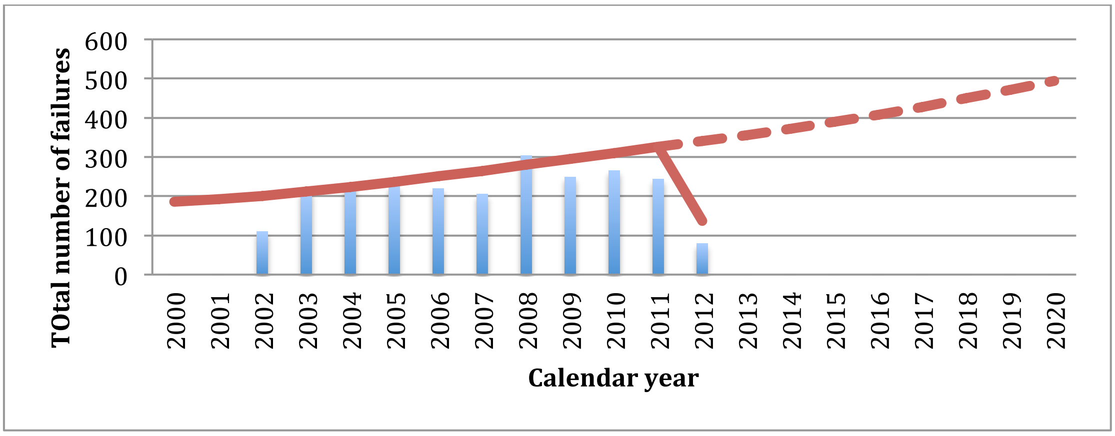



Figure 6-25 Total number predicted failures for all pipes

Based on the fitted hazard curves for each group, the probability of failures for each individual pipe at each age can be calculated.

Due to the computational capacity issue, this case study made a reasonable simplification. Only the pipes, whose probability of failures are higher than 0.01 during next 20 years, are considered in this case study. Therefore, only 2,344 pipes are left, and those pipes are used for the replacement decision optimisation analysis in the next section.

## 6.4 REPLACEMENT DECISION OPTIMISATION FOR GROUP SCHEDULING

### 6.4.1 Parameters for cost function and service interruption

***Parameters of Repair cost*** $C_{fail}$

For some types of failure, costs such as direct damage cost, water loss cost, indirect damage cost and social cost, were not accessible at this stage; in this case study, it is assumed that the failure cost is equal to repair cost.

The repair cost calculation relied on the repair history records, which was discussed in section 6.2.3. The pipe segments repair cost records had ten years of observation, with five different pipe materials, which were AC, CICL, DICL, MSCL, and UPVC.

A statistical analysis was conducted to analyse the relationships between the repair cost and materials as well as repair cost and diameter. Two box plots are illustrated in Figure 6-26 and Figure 6-27 to show different materials and diameters of repair cost data through the smallest cost, lower quartile, mean value, upper quartile, and the largest cost observation. Figure 6-26 illustrated that the repair cost shows dramatic differences between MSCL and the other materials. Three reasons caused the high repair cost of MSCL pipes: 1) the price of this material on its own was much higher than the other materials; 2) the repair methods and procedure utilized in MSCL pipes were more complicated than for the other pipes; 3) Most MSCL pipes are of larger diameters in the (>300mm), which induce higher cost. Moreover, the other materials showed a similar repair cost in this case, so that one can treat these four materials as one group, when the impact of material is taken into account.

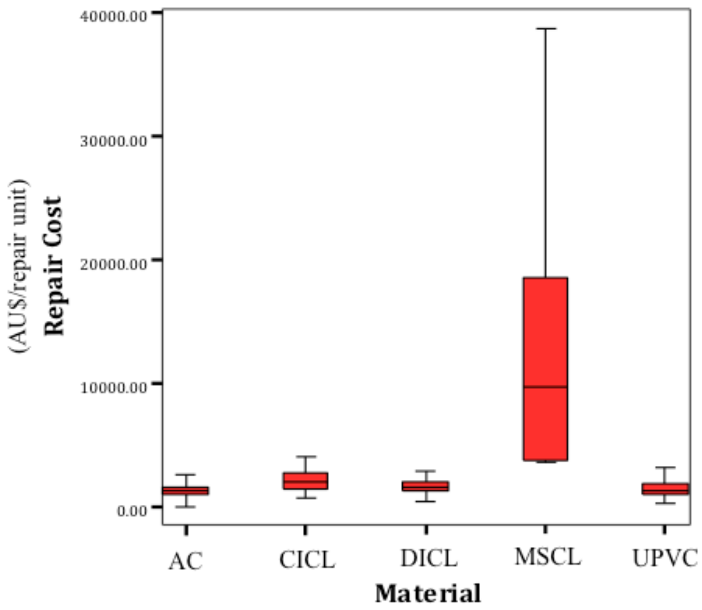



Figure 6-26 Repair cost by materials

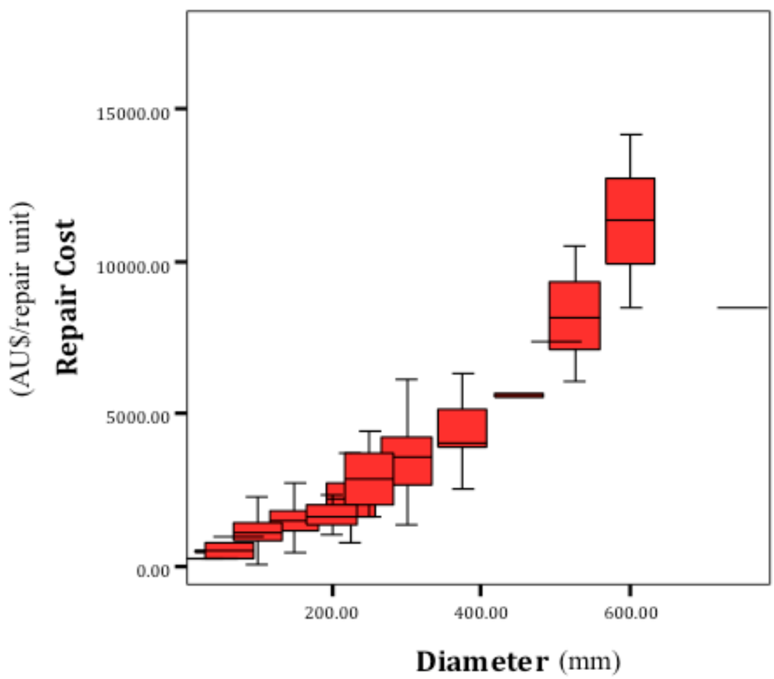



Figure 6-27 Repair cost by pipe diameter

Figure 6-27 showed that the repair cost increased with the increase in diameter, the similar trend shown in other research[65, 126]. Based on the repair data in this case, the relationship between the increase in the repair cost and pipe diameter was found to be of a nonlinear pattern.

The failure cost can be calculated using a sample nonlinear function Equation (4-2):

$$C_{fail} = a + b \cdot D_i{}^c,$$

where $D_i$ is the diameter of pipe $i$, and a, b, and c are the coefficients. A nonlinear regression was used to calculate the coefficients and showed in Table 6-5.

Table 6-5 Coefficients for repair cost function $C_{fail}$

| Material of Pipe | *a* | *b* | *c* |
|---|---|---|---|
| *AC, CICL, DICL, UPVC* | *477.201* | *0.066* | *1.849* |
| *MSCL* | *659.143* | *0.023* | *2.063* |

***Parameters of replacement cost***

Table 6-6 showed the replacement cost for water pipes, which is based on unit-length (one metre). As it showed, not all types of material were listed in Table 6-6 for the reason that there is an inevitable trend for some types of materials to gradually withdraw from the historical stage and be replaced by other types of pipes, for example, AC pipes may be replaced by PVC pipes and CICL pipes were alternated by DICL pipes.

Table 6-6 Water pipes length related replacement cost

| **Diameter (mm)** | **Substituted Material** | $Cr_i$ **(AU$/m)** | **Diameter (mm)** | **Substituted Material** | $Cr_i$ **(AU$/m)** |
|---|---|---|---|---|---|
| 90 | PVC | $98 | 900 | DICL | $2,575 |
| 100 | PVC | $104 | 960 | MSCL | $2,901 |
| 150 | PVC | $168 | 1000 | MSCL | $3,046 |
| 200 | PVC | $229 | 1050 | MSCL | $3,152 |
| 225 | PVC | $254 | 1085 | MSCL | $3,326 |
| 250 | PVC | $273 | 1200 | MSCL | $3,748 |
| 300 | DICL | $461 | 1290 | MSCL | $4,007 |
| 375 | DICL | $654 | 1350 | MSCL | $4,350 |
| 450 | DICL | $777 | 1500 | MSCL | $4,769 |
| 500 | DICL | $946 | 1650 | MSCL | $5,316 |
| 525 | DICL | $1,020 | 1800 | MSCL | $5,765 |
| 600 | DICL | $1,240 | 1950 | MSCL | $6,324 |
| 750 | DICL | $1,759 | 2159 | MSCL | $6,792 |

The factors affecting machinery cost remain unexplained in the current research. Therefore, it is assumed that machinery cost is determined by material types. The analysis of repair cost showed dramatic differences between MSCL and other materials. Considering these dramatic differences, the machinery cost was taken as M=AU$4,000/unit for MSCL and M=AU$2,000/unit for other materials. The distance-unit cost, $Cv_i$, was set to AU$100/km. The total budget for replacement of the whole water distribution network was AU$40 million for the next 20 years. Users based on their circumstances can change all these cost values.

***Customer interruption***

Customer interruption is a key factor, which is a concern for water utilities for their repair and replacement activities. In this case study, the water utility provided the information for customer interruption with Pipe ID, number of customers affected, $N_{C,i}$, customer types for each pipe, and the impact factors for customer types.

The classification of customer types was based on the population data from the water utility, which contained four types, CBD, High Density Urban, Urban and Rural. The category-specific impact factor $f_{C,i}$ is shown in Table 6-7.

Table 6-7 Category-specific Impact Factor

| Category | CBD | HIGH DENSITY URBAN | URBAN | RURAL |
|---|---|---|---|---|
| $f_i^C$ | 4.43 | 3.43 | 2.26 | 1.00 |

The duration of service interruption of each replacement pipe *i*, $Dr_{C,i}$, depends on the workload and work efficiency. In practice, the workload and efficiency is not only related to the machinery and skilled labour, but also relies on the diameter and length of pipes. In this case study, the duration per metre replacement $Dr_C$ is assumed and listed in Table 6-8.

Table 6-8 Service Interruption Duration

| Diameter (mm) | <300 | 300-900 | >900 |
|---|---|---|---|
| $Dr_C$ hour/meter | 1 | 2 | 3 |

## 6.4.2 Judgment matrix

In this case, the maximum geographic distance $\gamma^*$ was determined through calculating the distance between the nine maintenance centres. The minimum distance among the nine maintenance centres was 8.6km. Replacement of one group of pipes is assumed be accomplished by only one maintenance team from only one maintenance centre. Therefore, the maximum geographic distance $\gamma^*$ was assumed to be 4.3km.

The answers to the question, "which types of machinery are suitable for particular pipes?" rely on the expert knowledge of the engineers from water utilities and replacement contractors. All replacement activities, in this case study, are assumed be open trench replacement, so that the machinery utilised for each pipe relies on the pipe's diameter and material. To simplify this relationship, the machinery utilisation is treated following the hazard statistical grouping results calculated in section 6.3, which means that replacement pipes in the same hazard group can use the same machinery. Therefore, if pipe $i$ and pipe $j$ in the same hazard group, $\varepsilon_{ij}^{EU} = 0$, otherwise, $\varepsilon_{ij}^{EU} = 1$.

Since the water utility in this case study cannot provide any hydraulic information, therefore, if pipe $i$ and pipe $j$ share the same node (for example, valves), $N_{c,i,j} = \max(N_{c,i}, N_{c,j})$, otherwise $N_{c,i,j} = 0$.

Based on the group scheduling analysis, the judgment matrix for the 2,344 pipes, which is a "2344 by 2344" matrix with square matrix with values between 0 and 1, which showed in Figure 6-28 with colours, black indicated "0" and red indicated "1".

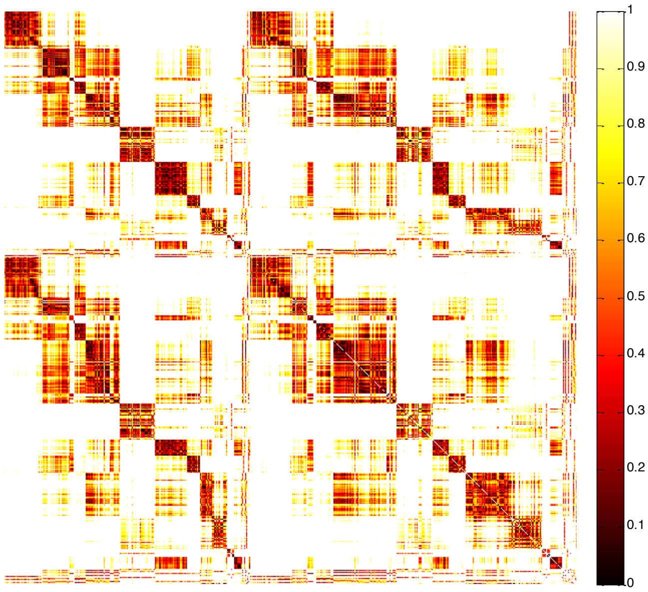



Figure 6-28 Judgment matrix

### 6.4.3 Parameters for the modified NSGA-II

The modified NSGA-II was given integer-valued decision variables. The population size, *pop,* is set as 100, the maximum generation is set as 500. 2,344 pipes are considered ($n = 2{,}344$), therefore, there are 2,344 design variables. Maximum number of pipes in each group, $gmax = 5$. Therefore the lower and upper bounds are $\mathbf{x}^{(L)} = [1, \dots, 1]$, and $\mathbf{x}^{(U)} = [2{,}344, \dots, 2{,}344]$. The number of objective function is 2.

A crossover probability of $p_C = 0.8$ and in the mutation operator, the standard deviation $\sigma_j = 2$, $\rho = 0.3$. In the selection operator, the selective pressure, $SP = 1.1$.

### 6.4.4 Results and discussions

Figure 6-29 provided the Pareto-front of the optimized solution for group scheduling replacement. Vertical and horizontal axes indicate the values of the two objectives, minimizing total life-cycle cost and minimizing service interruption impact, respectively. The AU$40 million budget is marked with red solid line. The area inside the Pareto-front and the total budget line is the feasible solution area, which means that all solutions located outside of this area are impossible or unacceptable.

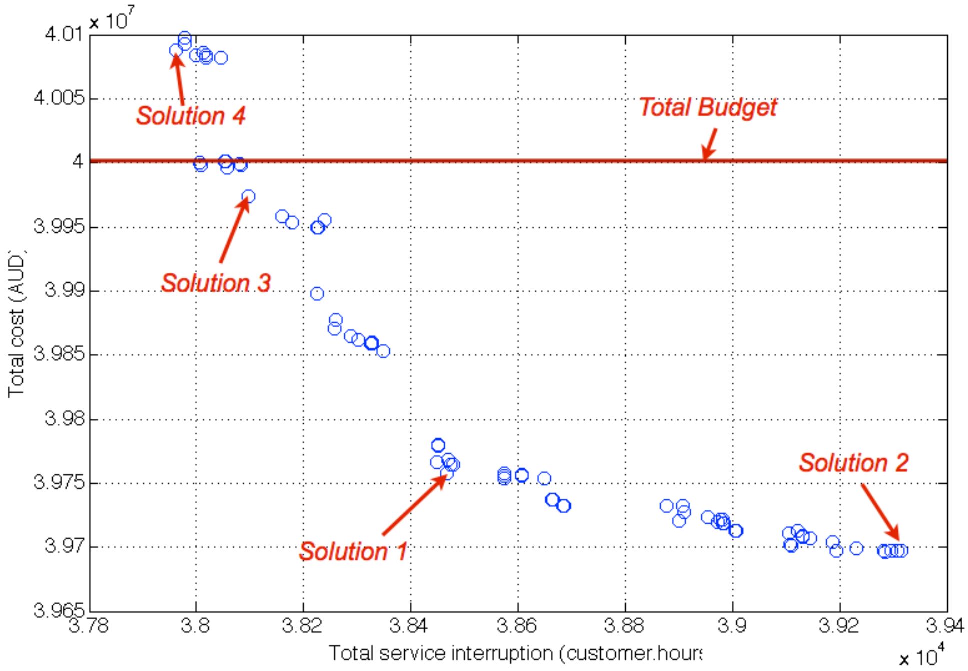


Figure 6-29 Pareto-front of optimized solution

Table 6-9 illustrates a summary of the selected five replacement planning solutions, Solutions 1 to 4 were marked in Figure 6-29, while the Non-group solution cannot be indicated in Figure 6-29 for its values are out of the scale boundary.

Solutions 1, 2 and 3 are all located on the Pareto-front of the feasible area. Compared with these selected three solutions, Solution 2 has highest total savings (AU$39,696,550) from budget, but has highest service interruption impact (39,316hours); Solution 3 has the lowest total savings (AU$39,973,700) from budget, but has lowest service interruption impact (38,097 hours); and Solution 1 has a trade-off between the total savings and service interruption impact, with AU$39,780,450 and 38,452hours. Solution 4 locates outside the feasible area, for it costs $40,093,300, which exceeds the total budget by AU$37,978.

Table 6-9 Summary of the Selected Replacement Planning Solution

| | Solution 1 | Solution 2 | Solution 3 | Solution 4 | Non-group |
|---|---|---|---|---|---|
| Total Number of Pipes | 795 | 736 | 803 | 810 | 804 |
| Total length of replacement (km) | 233.89 | 217.60 | 233.32 | 239.8. | 234.32 |
| Total Number of Replacement Group | 667 | 612 | 689 | 659 | 804 |
| Total Service Interruption Impact (10^3 h) | 38.452 | 39.316 | 38.097 | 37.978 | 43.325 |
| Total Investment in Replacement (Million AU$) | 39.780 | 39.697 | 39.974 | 40.093 | 41.940 |
| 0Total Savings from Budget | 219.55 | 303.45 | 263.00 | -93.30 | -1939.00 |

| (10^3 AU$) | | | | | | |
|---|---|---|---|---|---|---|

An optimization of replacement planning without considering grouping schedule (non-group schedule) was also conducted for comparing the results of the group scheduling replacement planning. The lowest expected total investment of non-group schedule was AU$41,939,000, which is AU$1,939,909 greater than the total budget (AU$40 million). Moreover, for non-group schedules, the total service interruption impact can be as high as 43325hours.

Table 6-10 provides the details of the replacement planning of Solution 1 from 1st to 20th year.

Table 6-10 Summary of the replacement planning of Solution 1

| Y | Total Number of Pipe | Total length of replacement (m) | Total length of replacement | Total Number of Replacement Groups | Total Service Interruption Impact (h) | Total Investment in Replacement (AU$) |
|---|---|---|---|---|---|---|
| **1** | 7 | 2614 | 1.12% | 7 | 338.6 | 444,593 |
| **2** | 12 | 3526 | 1.51% | 12 | 580.4 | 599,707 |
| **3** | 11 | 2875 | 1.23% | 11 | 532.0 | 488,984 |
| **4** | 26 | 8307 | 3.55% | 25 | 1,257.5 | 1,412,866 |
| **5** | 25 | 7224 | 3.09% | 21 | 1,209.2 | 1,228,668 |
| **6** | 30 | 8627 | 3.69% | 30 | 1,451.0 | 1,467,292 |
| **7** | 39 | 12278 | 5.25% | 31 | 1,886.3 | 2,088,260 |
| **8** | 65 | 18649 | 7.97% | 52 | 3,143.9 | 3,171,848 |
| **9** | 63 | 19987 | 8.55% | 55 | 3,047.1 | 3,399,417 |
| **10** | 67 | 17031 | 7.28% | 55 | 3,240.6 | 2,896,656 |
| **11** | 90 | 26809 | 11.46% | 67 | 4,353.1 | 4,559,712 |
| **12** | 70 | 19697 | 8.42% | 48 | 3,385.7 | 3,350,093 |
| **13** | 67 | 19212 | 8.21% | 57 | 3,240.6 | 3,267,604 |
| **14** | 64 | 17764 | 7.60% | 51 | 3,095.5 | 3,021,326 |
| **15** | 52 | 17041 | 7.29% | 46 | 2,515.1 | 2,898,357 |
| **16** | 41 | 11317 | 4.84% | 36 | 1,983.1 | 1,924,811 |
| **17** | 32 | 11247 | 4.81% | 30 | 1,547.8 | 1,912,906 |
| **18** | 17 | 5260 | 2.25% | 17 | 822.2 | 894,628 |
| **19** | 17 | 4423 | 1.89% | 16 | 822.2 | 752,270 |
| **Total** | 795 | 233888 | 100% | 667 | 38,452 | 39,780,450 |

Table 6-11 shows the details of the first year replacement planning of Solution 1. 7 pipes should be replaced in seven grouped replacement activities, which means that the seven pipes should be replaced individually.

Table 6-11 Details of the first year replacement planning of Solution 1

| Group No. | Asset key (Pipe ID) | Length of pipe |
|---|---|---|
| 1 | 530589 | 325.44 |
| 2 | 519636 | 238.99 |
| 3 | 525748 | 732.63 |

| | | |
|---|---|---|
| 4 | 1091733 | 239.58 |
| 5 | 500010 | 278.16 |
| 6 | 533172 | 172.63 |
| 7 | 500237 | 626.52 |

For the seventh year replacement planning, a greater value of pipe numbers compared with group number can be noticed, which means some pipes should be grouped together as one replacement activity. Table 6-12 listed 11 pipes at the seventh year of Solution 1. For example, pipes with asset keys "507185" and "512619" should be treated in one group, and pipes with asset keys "512183" and "513351" and "529450" should be grouped as well.

Table 6-12 Examples of the seventh year replacement planning of Solution 1

| Group No. | Construction Date | Material | Diameter | Pipe Length |
|---|---|---|---|---|
| 1 | 01/07/1997 | UPVC | 100 | 172.1153 |
| 1 | 01/07/1979 | AC | 100 | 144.9601 |
| 2 | 01/07/1980 | AC | 100 | 469.2863 |
| 3 | 01/07/1974 | AC | 100 | 193.6723 |
| 3 | 01/07/1984 | AC | 100 | 96.2167 |
| 3 | 01/07/1968 | AC | 225 | 92.8967 |
| 4 | 01/07/1995 | UPVC | 150 | 208.6306 |
| 4 | 01/07/1987 | AC | 100 | 381.8578 |
| 5 | 01/07/1988 | AC | 225 | 1094.0596 |
| 6 | 01/07/1992 | UPVC | 100 | 300.8922 |
| 7 | 01/07/1957 | AC | 100 | 416.1085 |
| … | … | … | … | … |

## 6.5 DISCUSSIONS

This case study followed the three-step process: (1) a data pre-analysis to investigate the provided data, to exclude invalid data, and to analyse the general characteristics; (2) a statistical grouping-based hazard prediction analysis to partition data into different subgroup based on their homogeneity, to calculate empirical hazard for each subgroup, and to fit hazard curve for failure prediction; (3) a replacement decision optimisation for group scheduling that gives an optimised replacement planning, taking total cost and customer interruption into consideration.

The first part, data pre-analysis, filtered the real data from the water utility and discarded the invalid data. A summary of the water pipe network was delivered. In the second part, seven pipe groups for hazard calculation were developed based on the statistical grouping analysis, followed by the hazard prediction for the seven groups. The probability of failure for each individual pipe was predicted. Then to simplify the computation, pipes with high probability of failures were retained for the replacement optimisation analysis.

The third part, replacement optimisation analysis, provided a graph (Figure 6-29) of Pareto-front of the optimized solution for replacement planning of group scheduling. Figure 6-29 showed a feasible solution area, which considered the trade-offs between the two objectives. Replacement operators can make decisions based on their own requirements by selecting one solution located in the Pareto-front, from which the five representative solutions were listed in Table 6-9 for comparison. The results illustrated that the group scheduling solutions (Solution 1, 2 and 3) can reduce the total life-cycle cost for approximately 5% compared with the non-group scheduling solution. Moreover, replacement group scheduling also contributes to dealing with overlapping water discontinuity areas. As a result, the total service interruption impact can dramatically shrink approximately 11.25%.

# Chapter 7: Conclusions and Future Work

Water pipeline replacement plays a vital role in controlling water pipe failures, infrastructure budgeting, and the level of services to the community. Reliability analysis and replacement optimisation lead to better replacement scheduling of water pipelines. This candidature has developed practical models and methodologies for water pipelines to provide advanced economic replacement schedules to meet the requirements of reduced costs and service interruptions.

After an extensive literature review, the candidate identified the following limitations in the work conducted to date:

(1) From a thorough literature review, it appears that the optimisation of group replacement scheduling of water pipelines has not been modelled previously. Existing models and methodologies have primarily focused on individual/single pipes to provide replacement schedules, which deliver an optimal replacement time. These methodologies do not satisfy the requirements of group replacement schedules of pipelines that would improve replacement efficiency and reduce replacement costs.

(2) Sometimes, evolutionary algorithms are applied to optimise replacement scheduling. However, these algorithms do not cater for group scheduling of pipes. They are only valid for individual/single pipes. The optimisation of scheduling groups of pipes needs to consider both time and space domains, while the work involving evolutionary algorithms have only focused on the time domain.

(3) In reliability prediction, existing hazard-based modelling methods have limitations when applied to real-world water pipes. They are limited when it comes to handling multiple failure characteristics, mixed failure distributions as well as lifetime data that would be truncated.

In this thesis, the candidate endeavoured to overcome these limitations and developed the following **new methodologies/models**:

(1) An optimization model for group replacement schedules of water pipelines - referred to as **RDOM-GS.** RDOM-GS integrates reliability analysis, cost

analysis, service interruption analysis, and optimization analysis to deliver optimal water pipes group replacement schedules, in terms of reduced service interruptions and total life-cycle costs.

(2) A modified NSGA-II to deal with the challenges of the allocations of pipelines for group replacement scheduling.

(3) An improved hazard-based modelling method for predicting the reliability of water pipelines taking into account multiple failure characteristics, mixture of failure distributions, and truncated lifetime data.

This chapter summarises the candidate's work and highlights its contributions to the knowledge in reliability analysis and replacement decision optimisation of water pipelines. Future research directions are also discussed.

## 7.1 SUMMARY OF RESEARCH

This candidature developed an optimization model for group replacement schedules of water pipelines, known as **RDOM-GS** with the following components:

- Three criteria of group scheduling which considers geographic distance, machinery utilisation and service interruptions a judgment matrix is used to quantify these three criteria.
- A cost model including repair cost, replacement cost and the net present value of total cost that considers the effects of group scheduling.
- A model of service interruption, which calculates customer impact due to each replacement activity. The impact is derived using the number of customers, the type of customers and the duration of the interruption.
- A modified NSGA-II, which deals with multi-objective replacement optimisation considering group scheduling. The modification contains a new designed encoding method to present the group number and replacement year of each pipe, a crowding distance operator to enhance the diversity in the solutions of the Pareto-optimal set, a mutation operator to keep pipes scheduled in one group that can be replaced in the same year.

This candidature also developed an improved hazard-based modelling method for water pipe reliability analysis, which comprises three components.

- The first component is a grouping algorithm using regression trees and expert rules, which partitioned the total number of water pipes into relatively homogeneous groups. This algorithm was validated using a case study based on selected water pipes data sets from a water utility.
- The second component is a suitable empirical hazard formula for water pipes derived from one of two different hazard formulas. The appropriate function was selected by the investigation of their different application impacts based on theoretical analysis and simulation experiments.
- The third component is a modified empirical hazard function to deal with the underestimation effects due to truncated lifetime data, which was validated using a Monte Carlo simulation framework developed in the candidature and which was based on a real water utility. Test-bed sample data sets were generated based on the main features of the real data of a water utility to test and validate the proposed improved empirical hazard function.

Both **RDOM-GS** and the **improved hazard-based model** was evaluated using a case study based on the maintenance of a local water utility responsible for almost 3,000 km of underground water pipes to test and apply the two models. The case study started with a data pre-analysis to ensure the quality of data, and analysed the age profile as well as repair history of the water pipes. A grouping analysis was presented using the grouping algorithm to partition pipes into seven groups. The empirical hazards were calculated followed by the parameters estimation for each partitioned group. RDOM-GS was utilised to optimise the replacement decision based on group scheduling.

## 7.2 RESEARCH CONTRIBUTIONS

This thesis presents several contributions in the field of optimisation for replacement scheduling of water pipelines and hazard modelling for reliability prediction. Three of these major contributions are summarised in the following subsections.

### 7.2.1 Multi-objective multi-criteria optimisation for group replacement schedules

This candidature developed RDOM-GS, which considered multiple optimisation objectives and multiple scheduling criteria. RDOM-GS has the following four characteristics:

*Multi-criteria group scheduling for water pipeline replacement*

Water pipeline replacement is usually scheduled in groups manually in order to reduce cost. However, research into group scheduling for water pipeline replacement considering multiple criteria for optimisation appears to be absent in the literature. The proposed RDOM-GS fills this gap by considering three criteria: geographic distance, machinery utilisation and service interruption, which are quantified by the judgment matrix.

*Cost model for groups of pipelines*

The new cost model considers the trade-off between repair costs and replacement costs. The Repair cost function was developed through the analysis of real repair cost data using nonlinear regression, while the Replacement cost function was developed considering length related cost, machinery cost and transportation cost. Each component can be altered with different group scheduling solutions. The total cost is the sum of repair costs and replacement costs considering failure probability and Net Present Value (NPV) – the latter, which is applied as one of the objectives of the replacement optimisation.

*Customer interruption model for groups of pipelines*

Similar to the cost model, despite a thorough literature search that evidence of research work on customer interruption factors for group scheduling is missing. In this candidature, a new customer interruption model, which considered the number of customers interrupted, the type of customers and the duration of interruption was developed as part of RDOM-GS. This service interruption model integrates failure probability and the customer impact caused by groups of pipes.

*Optimisation algorithm for scheduling groups of pipelines*

Group scheduling for water pipeline replacement optimisation is complex, as it needs to consider a large number of decision variables, which are in both time and space domains. Existing optimisation methods cannot be applied directly to deliver optimal solutions. RDOM-GS integrates a modified NSGA-II to deal with this multiple criteria and multiple objective optimisation problems. The modified NSGA-II enables RDOM-GS to deliver schedules in order to limit service interruptions and to minimize total life-cycle cost. Results from a comparison study showed that the modified NSGA-II produced better optimised replacement schedules, with lower total cost, lower service interruption and greater diversity in the solutions of the Pareto-optimal set.

### 7.2.2 Improved Hazard modelling methods for water pipelines

The improved hazard modelling method, developed in this candidature, contributes to the knowledge of reliability prediction for water pipelines in three aspects:

***A systematic grouping algorithm for water pipes***

The grouping algorithm developed in this candidature can effectively analyse water pipe data with multiple failure distributions. The four-step procedure of the statistical grouping algorithm consists of (1) an age-specific material analysis to calculate the number of failures per unit-length over average age for each material type; (2) length related pre-grouping; (3) regression tree analysis to partition pipe data considering material type, diameter and length; and (4) grouping criteria adjustment based on knowledge rules.

Using this procedure, pipe data can be partitioned into relatively homogeneous groups, and sufficient sample size of failure data for each group can be guaranteed. Based on the grouping algorithm, the hazard curves between groups can be clearly distinctive from each other; hence, more accurate hazard prediction results for each group of pipes can be derived.

***Critical evaluation of two frequently used empirical hazard formulas***

The differences of application impacts between two commonly used empirical hazard formulas $\widehat{h1}_i$ and $\widehat{h2}_i$ (Equations (3-9) and (3-10)) have not been clearly reported in the literature. Overlooking this difference may result in inaccuracies in the calculations. This candidature conducted a comprehensive evaluation on estimated performance of the two formulas against true hazard function values through theoretical analysis and simulations, with the following conclusions:

1) $\widehat{h2}_i$ is a finite approximation of average failure rate (AFR), whereas $\widehat{h1}_i$ is a finite approximation of the instantaneous failure rate. However, when time interval $\Delta t$ approaches zero, both $\widehat{h1}_i$ and $\widehat{h2}_i$ converge to the true hazard function;

2) Theoretically, the difference between formulas $\widehat{h1}_i$ and $\widehat{h2}_i$ is significant. $\widehat{h1}_i$ underestimates the true hazard function values in most cases and the

underestimation is substantial, while $\widehat{h2}_i$ gives much less biased estimation of the true hazard function than $\widehat{h1}_i$;

3) For data analysis purposes, the underestimation of $\widehat{h1}_i$ is much more sensitive to the change of time interval $\Delta t$, while $\widehat{h2}_i$ is almost not affected. Therefore, for calculating empirical hazard function of continuous-time failure data, if the maximum failure rate over the time interval periods is less than 0.1, both formulas are good estimators of the true hazard function values. Otherwise, $\widehat{h2}_i$ has a higher accuracy result than $\widehat{h1}_i$ for calculating the empirical hazard function.

***Modified empirical hazard model considering truncated lifetime data***

The field lifetime data for water pipes is often truncated. This truncation results in the underestimation of the true hazard when calculating the empirical hazard. The modified empirical hazard function based on pipe segmentation considers three types of pipe segments: survived pipe segments, repaired pipe segments and new pipe segments. The Monte Carlo simulation framework developed in this candidature enables to generate test-bed sample data sets in terms of the main features of the real data of a water utility. By applying this simulation framework to generate test-bed sample data, the modified empirical hazard function has been verified that it can effectively reduce the underestimation effects caused by truncated lifetime data, by can effectively reduce the underestimation effects caused by the interval truncation of lifetime data.

### 7.2.3 Application of the proposed models in a real case study

The real case study involved the application of the proposed improved hazard model and RDOM-GS to a water utility responsible for almost 3,000 km of water pipelines. All pipelines were partitioned into seven groups using the grouping algorithm. For each group, the calculated empirical hazards were calculated in specific patterns. The real values of the number of failure in each calendar year showed that the proposed improved hazard-based modelling method provided good estimation results for water pipe failure prediction.

Application of the RDOM-GS resulted in a Pareto-optimal set and a set of scheduled replacement activities, which included the information of the water pipe's unique ID, group number, replacement year, total cost and total service interruption.

Additionally, total life-cycle costs reduced by AU$ 2.16 million (approximately 5%) compared with the non-group scheduling solution, and total service interruptions shrunk by11.25%.

## 7.3 FUTURE RESEARCH DIRECTIONS

The RDOM-GS and the improved hazard modelling method can be further improved or extended as follows:

### 7.3.1 Extension of multi-objective RDOM-GS

This candidature provides a model of optimisation for group replacement schedules of water pipelines. Two objectives were considered as minimum the total life cycle costs and service interruption impacts. However, there are some other important issues for water utilities that need to be considered for replacement scheduling, for example, the leakage of water pipeline caused high levels of non-revenue water (NRW). High levels of NRW are detrimental to the financial viability of water utilities, as well to the quality of water itself. Therefore, the RDOM-GS can be further extended considering improvement of water quality or hydraulic performance.

Moreover, current RDOM-GS considered pipeline replacement as replacing the whole length of pipeline. However, for some pipelines, especially those of long length, replacement of one part of the pipe rather than the whole length seems more reasonable, because failures may only happen in a small area rather than being distributed over the whole length. This improvement requires the failure records to be more precise in positions and locations.

### 7.3.2 Extension of hazard modelling method for water pipes

The candidate developed an improved hazard modelling method to improve the existing hazard model [13] in satisfying three aspects: the requirement for partitioning pipe into relatively homogeneous groups based on specific features of water pipes, the requirement for dealing with underestimation effects caused by truncated lifetime data, and the requirement for differentiating two commonly used empirical hazard formulas. However, failure, in this candidature, is only considered as general failure, which is not categorised based on different specific failure modes. Different failure modes might be caused by different reasons, that may lead to different types of works, e.g. repair, inspection, condition monitoring. Therefore, hazard-modelling methods can be further extended to predict the reliability of a water pipe system in the following scenarios:

- Hazard modelling method considering multiple failure modes (e.g. break, rupture, leakage, corrosion)
- Hazard modelling method with multiple types of works (e.g. repair, inspection)

Moreover, the generation of the simulation samples based on the proposed Monte Carlo simulation framework is efficient for practical data analysis purpose. However, this simulation has only considered pipe length as pipe's feature. This simulation sample generation algorithm may be further developed for testing the impact of possible covariates e.g. material types, diameter and soil types on the asset failure patterns in the future.

### 7.3.3 Application to other linear assets

Water pipelines are linear infrastructure assets. All linear infrastructure assets have similar features, such as being spanned in long distances, various working environments, having different failure rates, and replacement considering group scheduling. These features lead to similar methods for all linear assets to deal with hazard calculation and replacement optimization, compared with the methods for water pipelines. Therefore, the proposed improved hazard model and the RDOM-GS have the potential to optimize maintenance planning in other linear asset networks such as electricity distribution, railway networks and road networks.

## 7.4 FINAL REMARKS

In today's market, water utilities strive to operate under ever-increasing cost pressures. Water pipelines are the largest investment for water utilities. The majority of water utilities today focus their operations on optimizing water pipeline maintenance to reduce costs. As mentioned in the introductory chapter of this thesis, maintenance costs have increased dramatically to a level that utilities can no longer absorb.

Optimisation for group replacement schedules of water pipelines should consider a multitude of criteria and factors including risk, service interruption, network reliability, resource availability and costs, pipe specifications, and technology to be employed.

The methodologies and models reported in this thesis would enable maintenance planners to develop group replacement schedules of groups of pipelines based on multiple group scheduling criteria considering multiple objectives.

The outputs of this candidature have the potential to optimise replacement planning in other linear asset networks such as electricity distribution, railway networks and road networks, resulting in bottom-line benefits for end users and communities.

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